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A COMPARATIVE STUDY OF NON-LINEAR FORECAST COMBINATION OF RAINFALL-RUNOFF MODELS USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

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Abstract: Rainfall-runoff modeling is important in flood forecasting systems. Although, a wide variety rainfall-runoff models has been developed and applied, but it cannot be claimed that there is one model which can perform satisfactorily at all times or under all conditions. Instead of switching models from one to another, this study proposes combining the simple linear rainfall-runoff model results. This study presents the development of five combination methods, simple average method (SAM), the weighted average method (WAM), the fuzzy system method (FSM), the neural network method (NNM) and the adaptive neuro-fuzzy inference system method (ANFISM) to combine the simulated results of three different rainfall-runoff models called single linear model (SLM), Linear Perturbation Model (LPM) and Linearly Varying Gain Factor Model (LVGFM) on four catchments. Comparison of the estimated runoff results reveals that the ANFIS combination method performs better than the other combination methods and is the best individual rainfall-runoff model. Furthermore, the ANFIS combination method provides improved flood estimates and is recommended for use as the combination system for flood forecasting that can also be used by engineers and hydrologists.

Key Words: Rainfall-Runoff models, Combination methods, Fuzzy sets, Neural networks, ANFIS

1. INTRODUCTION

Quantitative modeling of rainfall-runoff processes is often a requirement for optimal design of water storage and drainage networks or for forecasting and managing extreme events such as floods. The complexity of rainfall-runoff relationships is well recognized and represents a significant challenge to hydrologists (Beven, 2001). The typical heterogeneity of the geomorphologic characteristics of the watershed (such as soil type, vegetation cover, etc.) and the spatial and temporal variations of model inputs (such as rainfall patterns) and initial conditions in the model are some of the reasons leading to the complexity in rainfall-runoff modeling and this complexity can introduce the problem of overparameterization (Beven, 1989).

Hydrologists have focused on rainfall-runoff modeling issue from two different points of view: knowledge-based modeling and data-based modeling (De Vos & Rientjes, 2005). Knowledge-based rainfall-runoff modeling describes the system and processes involved in producing runoff in a physically realistic manner. The best examples of knowledge-driven modeling are physically-based model approaches (e.g. Ewen et al., 2006; Du et al., 2007). Physically-based modeling has some significant shortcomings, like considerable input requirements, and large computational demands. Conceptual models (e.g. Lee et al., 2005; Jonsdottir et al., 2006) are in-between physically-based models and empirical models, and they present physical processes in a more simplified form, while an empirical model, on the other hand, is built upon observation of input and output, without seeking to represent explicitly the process of conversion. Most of conceptual models still have a lot of parameters, and the user's familiarity with the model will influence the quality of the model predictions.

The data-based or data-driven approaches extract information from hydrological data to forecast runoff with almost no consideration to the physical laws. Beven (2001) stated that "If we can successfully relate the inputs to the outputs, why worry about what is going on inside the catchment box?" This approach to rainfall-runoff modeling covers a variety of methods like, time series (e.g. Kim & Delleur, 2001; Niedzielski, 2007), empirical regression (e. g. Jain & Prasad Indurthy, 2003; McIntyre et al., 2007), fuzzy rule-based systems (e. g. Ozelkan & Duckstein, 2001; Tayfur & Singh, 2006) and artificial neural networks modeling (e. g. De Vos & Rientjes, 2005; Pan et al., 2007), generally derived from statistics and artificial intelligence. The data-based rainfall-runoff models require no information about the physical processes of rainfall-runoff transformation. However, they cannot perform appropriately without access to a large dataset.

Recently, technology development and computational power enhancement have helped to develop a number of rainfall-runoff models with different levels of involved processes covering. Regardless of these progresses, there is no assurance that one of these models will predict a flood event in different climate situations and different kinds of watersheds better than the others (Shamseldin & O'Connor, 1999).

Rainfall-runoff modeling is important in river flood forecasting systems. In order to forecast floods, the user must make a choice between the available models. Information on data availability, model complexity, familiarity with the model, and required accuracy can help a user to select a rainfall runoff model. However, because the accuracy of flood forecasts has significant socio-economic consequences, it may be advantageous to combine several model forecasts. The combination process will allow a user to capitalize on the various rainfall-runoff models' strengths. A schematic diagram of the process of combining different rainfall-runoff models is shown in Figure. 1 where R_j^2 denotes the Nash-Sutcliffe simulation efficiency of model-j, and R_c^2 denotes the Nash-Sutcliffe simulation efficiency of the combination method.

Although the combination of models concept has been widely used in fields as diverse as economics, statistics, and weather forecasting, it has received little attention in hydrologic forecasting or simulation studies. McLeod et al (1987) reported the first experiments dealing with the combination of river flow forecasts using a Box & Jenkins (1970) time series models and a conceptual rainfall-runoff model. Shamseldin et al (1997) in a seminal work tested three combination methods, the simple average method, the weighted average method, and the neural network method to combine daily discharge estimates of five rainfall-runoff models for 11 catchments. Several studies have employed different combination methods for rainfall-runoff modeling. Table 1 provides a list of some of these studies.

Table 1. Some of combination methods applied for rainfall-runoff modeling

Robust weighted average method	Coulibaly et al., (2005)
Three artificial neural networks	Shamseldin et al., (2007)
Gene expression programming	Fernando et al., (2009)
Simple Average and Takagi-Sugeno fuzzy system	Zhang et al., (2009)
Bayesian model averaging	Liang et al., (2010)

Since Zadeh (1965) introduced fuzzy set theory to model complex systems, it has been applied extensively and effectively in different applications, such as data analysis, control processes, and pattern recognition. In water resources, fuzzy systems have been applied for optimization of reservoir flood control operation (Guangtao, 2008), river suspended sediment modeling (Kisi et al., 2006), river water quality simulation (Li et al., 2007), flood forecasting (Tareghian & Kashefipour, 2007), and river nutrient loads estimation (Buzas, 2001).

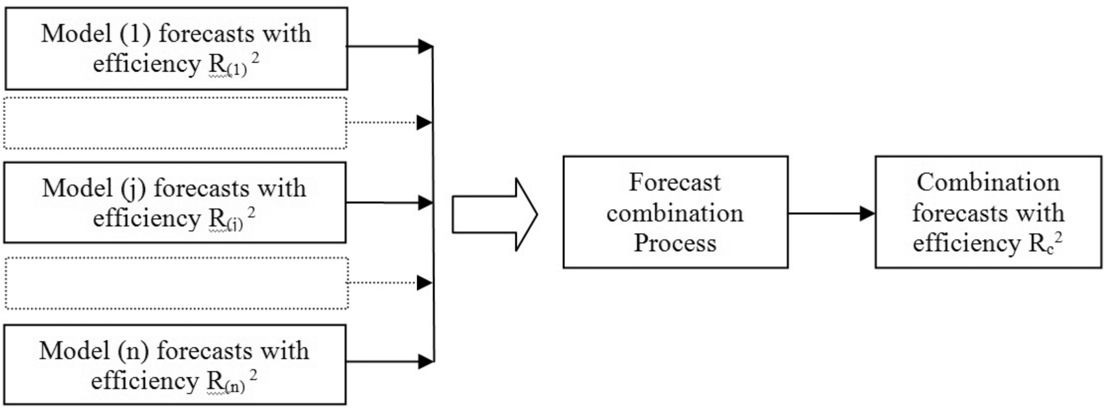

Figure 1. Schematic diagram for the procedure of combining forecasts of different rainfall-runoff models (Xiong et al., 2001)

By defining some fuzzy if-then rules, a fuzzy system can model the qualitative feature of human knowledge and reasoning processes. However, lacking of an effective method which can adjust the membership functions to minimize the result errors and maximize the model performance is apparent. On the other hand, artificial neural networks have the ability to learn from given patterns (input-output pairs), and use this ability as a solution for complex problems (Jang, 1993). As a result, we propose the adaptive neuro-fuzzy inference system (ANFIS) methodology for combining the results of rainfall-runoff models. The ANFIS is a multilayer feedforward network presenting an approach for combining the human-like reasoning style of fuzzy systems with the learning structure of neural networks. Capability of combining fuzzy systems and artificial neural networks strengths has made ANFIS an applicable method in hydrological studies such as prediction of water level in reservoirs (Chang & Chang, 2006), hydrological time series modeling (Keskin et al., 2006), and river flow estimation (Firat & Gungor, 2007), reconstructing missing flow data (Dastorani et al., 2010), modeling elevation-surface area-storage interrelationships (Fayaed et al., 2011), and rainfall forecasting (El-Shafie et al., 2011).

For combining the rainfall-runoff models outputs, the results of the neural network combination method (NNM) are found to be generally better than those of the linear weighting (WAM) and fuzzy-based methods (Shamseldin et al., 2007). However, ANNs have difficulty to extrapolate beyond the range of the data used for calibration (Shahin et al., 2008). Fuzzy logic enhances the generalization capability of a neural network to produce reasonable outputs from inputs that have not been employed during training (Matreata, 2006). In flood forecasting models, developing a model that have the ability to generalize and extrapolate is very important. Hence, in this study, we implemented ANFIS to examine the value of ANFIS as a combination method for combining the outputs of three simple Rainfall-Runoff models (SLM, LPM, and LVGFM) with least required information (just rainfall and runoff). The results of the proposed method will be compared with the performance of previously presented combination methods (SAM, WAM, NNM, and FSM). At the end, implementation of these individual and the combination of rainfall-runoff models in predicting an individual flood hydrograph and simulating the whole distribution of runoff will be examined.

2. MATERIALS AND METHODS

2.1. Combination methods

In this study, five methods of combining model outputs were considered, namely the simple average method (SAM), the weighted average method (WAM), the fuzzy system method (FSM), the neural network method (NNM), and the adaptive neuro-fuzzy inference system method (ANFISM). Hence, the output of three single rainfall-runoff models would be fed as inputs to the black-box combination models (i.e., NNM, FSM, and ANFISM), and observed runoff would be the output of the combination model. Here, the first four combination methods have been described briefly and they have been portrayed in detail by Shamseldin et al., (2007), Xiong et al. (2001), and Coulibaly et al., (2005), and the ANFIS structure have been described thoroughly.

2.1.1. The Simple Average Method (SAM)

The simple average method (SAM) is the simplest method of combining the outputs of different individual models. Given the estimated discharges of N rainfall-runoff models, a combined estimate of the discharge of the ith time period, using the SAM, is given by:

$$\hat{Q}_{C\,i} = \frac{1}{N}\sum_{j=1}^{N}\hat{Q}_{j\,i} \quad (1)$$

Equation (1) illustrates that the computation of the SAM combined output is very trivial, requiring very little effort and without any empirical curve fitting. Moreover, it highlights that equal emphasis (i.e. weight) is assigned to the outputs of all of the models being considered.

2.1.2. The Weighted Average Method (WAM)

When some of the individual models selected for combination appear to be consistently more accurate than others, the use of a weighted average would be considered. The weighted average method (WAM) for combining the estimated model outputs, in the case of N rainfall-runoff models, may be expressed as (Granger & Ramanathan, 1984),

$$Q_i = \sum_{j=1}^{N} \mathrm{a}_j \hat{Q}_{j\,i} + e \qquad (2)$$

Where Q_i is the observed discharge of the ith time period, a_j is the weight assigned to the jth model estimated discharge $\hat{Q}_{j_i}$ and e_i is the combination error term.

2.1.3. The Neural Network Method (NNM)

Whereas conventional methods show a mediocre performance, ANNs have been successfully applied in different aspects of engineering applications. ANNs have proved to offer a better way to model a system with complex input-output relationships in comparison with the other approaches. A common three layer feedforward type of artificial neural network has been shown in figure. 2.

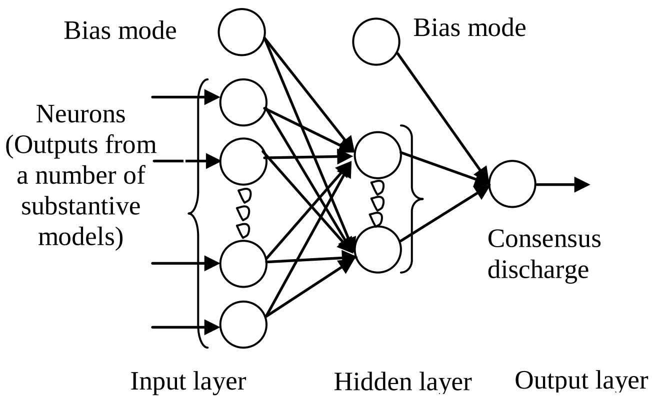

Figure 2. Schematic diagram of Neural Network Method (NNM)

The input dataset (x_i) is presented to the network (input layer neurons). After multiplication by connecting weights (v_{ij}) and association with biases (b_j) (i.e., $net_j = \sum x_i v_{ij} - b_j$), the output of each input layer node is sent to all nodes in the following layer (z_i). Through an activation function, an input vector to the output layer will be computed. A sigmoid nonlinear transfer function is commonly employed, f (net_j) = [1/ (1+e−net_j)]. Then, the output layer neurons act as like as hidden layer neurons. For each input pattern, the backpropagation algorithm uses the gradient descent method to adjust biases and connection weights to decrease the difference between measured and estimated outputs. Based on these differences, the backpropagation algorithm minimizes an error function (E) of the following form to find the optimal weights and biases.

$$E = \sum_P \sum_n (y_i - t_i)^2 \qquad (3)$$

Where y_i= component of a network output vector Y; t_i= component of a target output vector T; n= number of output neurons; and P= number of training patterns (Granger & Ramanathan, 1984; Tayfur & Singh, 2006). For more detailed information on the structure of NNM and how NNM can be used as a combination method, ASCE Task Committee (2000) and Shamseldin et al., (1997) can be reviewed.

2.1.4. The Fuzzy System Method (FSM)

In order to model a system with fuzzy sets, at the first level, all the variables (input or output) must be fuzzified through a membership function. The membership function defines the degree of partial belonging a variable to different portion of the reference set which it can be between 0 and 1 contradict with classic theory which it must be crisp value 0 or 1.

One of the advantages of the fuzzy systems is that one variable value can have a different membership degree in different linguistic terms. For example, a 500 m^3/s runoff would regard as an average runoff with 0.3 membership degree and high runoff with 0.6 membership degree. At the next level, in order to formulate fuzzy relations between input and output variables, rules with the IF…THEN format would be defined. For example, for flow forecasting based on existing rainfall and evapotranspiration, these rules can be defined:

IF rainfall is low and evapotranspiration is high THEN runoff is low;

IF rainfall is high and evapotranspiration is low THEN runoff is high…

Based on defined rules, a fuzzy inference system is used to formulate the transformation process of given inputs to the corresponding outputs. There are two types of fuzzy inference systems, 1- Mamdani, 2- Takagi-Sugeno. Nedjah & Mourelle (2005) provide detailed information on fuzzy inference systems. In this study, the Takagi-Sugeno fuzzy inference system was used.

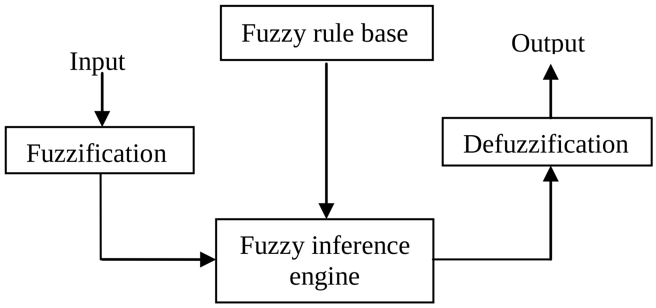

Figure 3. Schematic representation of fuzzy system method (FSM)

In the fuzzy inference process, after input variables fuzzification, defuzzification process is pursued to get the final output. Defuzzification process converts a fuzzy solution set to an understandable respond form (Mahabir et al., 2003). A schematic representation of fuzzy system has been shown in figure 3.

2.1.5. The Adaptive Neuro-Fuzzy Inference System Method (ANFISM)

The ANFIS is an extension of Takagi-Sugeno fuzzy model which facilitates learning and adaptation in the framework of adaptive systems (Jang, 1993). Two fuzzy if-then rules using the Takagi-Sugeno fuzzy inference systems are defined to describe the ANFIS architecture:

Rule 1. If (x is A_1) and (y is B_1) then ($f_1=p_1x+q_1y+r_1$),

Rule 2. If (x is A_2) and (y is B_2) then ($f_2=p_2x+q_2y+r_2$),

where A_i and B_i are the membership functions based on linguistic terms (low, average, high, and …) for x and y inputs, fi is the output function, and p_i, q_i and r_i are the linear consequent parameters. As it can be seen in figure. 4, ANFIS architecture comprises five layers. The node function of each layer is the same, and is as follows:

In layers 1 and 2, membership functions are used to fuzzify the inputs, and then, AND or OR operators are applied to compute the weight or firing strength (w_i) for each defined rule. Usually, the generalized bell-shaped is used as membership function and specified as:

$$\mu_{A_i}(x) = \frac{1}{1+\{((x-c_i)/a_i)^2\}^{b_i}} \quad (4)$$

where $\{a_i, b_i$, and $c_i\}$ are the antecedent parameters set. In layer 3, normalized firing strengths of each rule are calculated by dividing each rule's firing strength by summation of all rules' firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i} \quad (5)$$

In layer 4, the outputs of layer 3 are multiplied by the consequent of each fuzzy rule;

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad (6)$$

In layer 5, a single crisp value is computed as the network output, and the result of ANFIS network can be compared with the measured data:

$$O_{5,i} = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \quad (7)$$

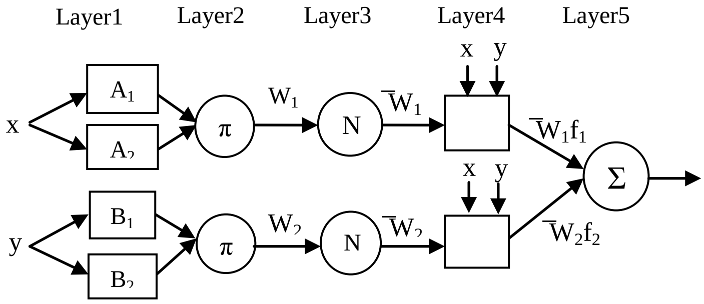

Figure 4. ANFIS Architecture

During training process, two different parameter sets, antecedent parameters $\{a_i, b_i$, and $c_i\}$ and consequent parameters $\{p_i, q_i$, and $r_i\}$ must be adjusted. A hybrid algorithm including the gradient descent method and least mean square estimation is used in the two phase learning procedure. In the first phase, input dataset are propagated forward. While the antecedent parameters are held fixed, the least mean square error is used to approximate consequent parameters. In the second phase, the output error is backpropagated through the network. The gradient descent method is employed to revise the antecedent parameters, while the consequent parameters are assumed to be set. To reach an acceptable error, the learning procedure will be continued iteratively. The iterative calibration of the rule consequents is achieved by means of the "linear least squares" method. The fact that the model output is a linear function of the consequent parameters is the main reason why this hybrid calibration procedure is attractive. The detailed information about architecture and algorithm of ANFIS can be found in Jang (1993).

2.2. Rainfall-Runoff Models

2.2.1. The Simple Linear Model (SLM)

The simple linear model was proposed by Nash & Foley (1982) as a primitive rainfall-runoff model. They assumed a linear time-invariant relationship between the total rainfall R_i and the total discharge Q_i. In a discrete non-parametric form, Kachroo & Liang (1992) expressed SLM by the following summation relation:

$$Q_i = \sum_{j=1}^{m} R_{i-j+1} h'_j + e_i \quad (8)$$

where Q_i and R_i are the discharge and rainfall respectively at the ith time-step, h'_j is the jth discrete pulse response ordinate or weight, m is the memory length of the system, and e_i is the output error term. For more simplicity, a new parameter, the gain factor G has been defined as the ratio of the total volume of observed discharge to observed rainfall to describe the long term runoff coefficient (Kachroo & Liang, 1992). When the measurement units of rainfall and runoff (e.g. mm/day over the catchment area) are same, then the gain factor G is expressed as a summation of the discrete pulse response ordinates:

$$G = \sum_{j=1}^{m} h'_j \qquad (9)$$

After the gain factor G was applied, runoff would be calculated by

$$Q_i = G\sum_{j=1}^{m} R_{i-j+1} h_j + e_i \qquad (10)$$

where h_j is the h'_j whose value reduced proportionately by the gain factor such that,

$$\sum_{j=1}^{m} h_j = 1 \qquad (11)$$

2.2.2. The Linear Perturbation Model (LPM)

Nash & Barsi (1983) used seasonal information of the observed rainfall and discharge series, and supposed that in a year which the rainfall is equal to its seasonal average, the associated discharge is also equal to its seasonal average. Nevertheless, if there is a difference between the rainfall and the discharge values and their related seasonal prospects, there will be a linear time-invariant system to relate these differences series which has a density summation form:

$$Q'_i = \sum_{j=1}^{m} R'_{i-j+1} h'_j + e_i \qquad (12)$$

where h'_j is the jth discrete pulse response ordinate relating to the difference series of input and the output, R'_i and Q'_i are the differences of rainfall and discharge from their seasonal prospects, m is the memory length, and e_i is the error output term.

2.2.3. The Linearly Varying Gain Factor Model (LVGFM)

Inconstant gain factor is the main difference between the linearly varying gain factor model (LVGFM) and SLM which is constant. Ahsan & O'Connor (1994) proposed the LVGFM for the single input to single output situation. The model output (runoff) using a linearly gain factor G will be expressed by:

$$Q_i = G_j \sum_{j=1}^{m} R_{i-j+1} h'_j + e_i \quad (13)$$

where $\sum_{j=1}^{m} h_j = 1$ the variable gain factor was intended to has a linear relation with the soil moisture state z_i ,

$$G_i = a + bz_i \qquad (14)$$

where a and b are constants. For the value of zi, Ahsan and O'connor (1994) put forward that z_i can be acquired from the outputs of the SLM by the relation:

$$z_i = \frac{\hat{G}}{\overline{Q}} \sum_{j=1}^{m} R_{i-j+1} \hat{h}_j \qquad (15)$$

where $\overline{Q}$ is the mean calibration discharge $\hat{G}$ and $\hat{h}_j$ are estimates of the gain factor and the pulse response ordinates of the SLM respectively.

3. Study Area

Four catchments with two different hydrological and climate conditions were selected in this study for comparing the results of individual and combination of rainfall-runoff models. The data used for model calibration and verification are daily rainfall and runoff series. The major hydrological characteristics of four catchments have been listed in table 2, and the location maps of study areas have been shown in figure 5.

4. Evaluation Criteria for Model Performance:

For rainfall-runoff models, the main criterion used for assessing simulation performance is the Nash-Sutcliffe efficiency index (1970), R^2 defined as:

$$R^2 = \frac{F_0 - F}{F_0} \times 100 \qquad (16)$$

where F is the sum of squares of differences between estimated and observed discharges, and F_0 is the sum of squares of differences between the observed discharges and the mean discharge during the calibration period.

Moreover, in order to objectively evaluate the model performance, one of the most commonly employed error measures, root-mean-square error (RMSE) was applied, and can be calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{m_i} - Q_{p_i})^2}{n}} \qquad (17)$$

where Q_m= measured runoff; Q_p= predicted runoff; and n= total number of data pairs considered.

5. Models Application and Development:

The four catchments data were used to build the three selected rainfall-runoff models (SLM, LPM and LVGFM). For SLM model calibrating, hj matrix must be determined. Based on Kachroo & Liang (1992), h_j can be calculated by,

$$H = (X^T X)^{-1} X^T Y \qquad (18)$$

where, X and Y are rainfall and runoff series respectively. The ordinary least squares (OLS) method was employed to estimate the discrete pulse response ordinates (h_j), and find the best size for h_j matrix. With trial and error, the best size for m was calculated as 20.

In the case of the LPM, two new series $R_i = x_i - x_d$ and $Q_i = y_i - y_d$ are defined. Where, x_d and y_d are the average daily rainfall-runoff for each series of data over the calibration period.

Table 2. Summary of hydrological data of the four selected catchments

Name	Area(Km^2)	Country	Data Length	Calibration Period
North Fork of Caspar Creek (Nfcc)	4.84	USA	1965.1.1-1973.12.31	1965.1.1-1970.6.22
South Fork of Caspar Creek (Sfcc)	4.24	USA	1964.1.1-1975.12.31	1964.1.1-1972.3.17
Gronwen	0.7	Wales	1964.1.1-1969.3.28	1964.1.1-1967.7.22
Teifi	893.6	Wales	1965.1.1-1993.12.31	1965.1.1-1984.2.29

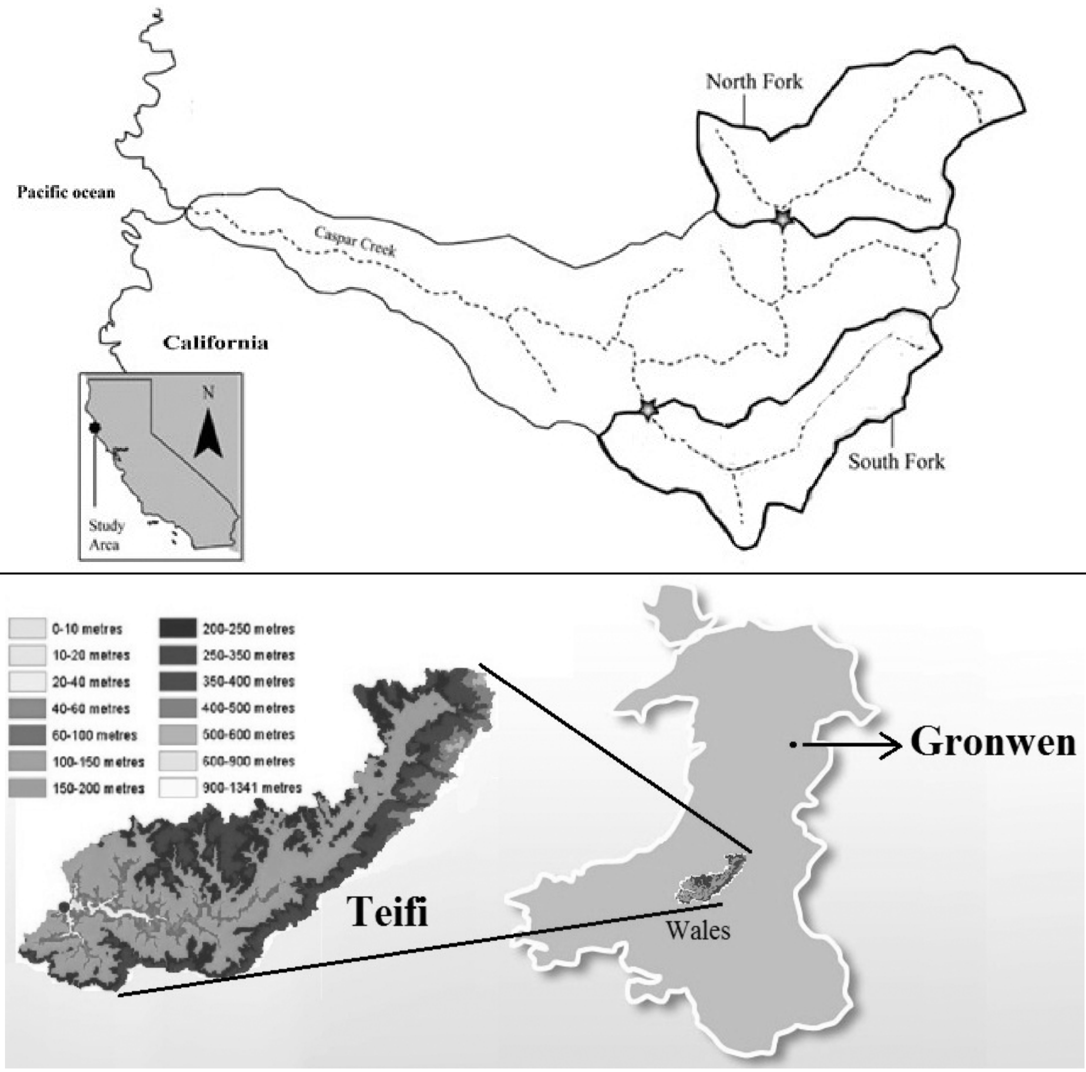

Figure 5. Location map of Nfcc& Sfcc in California “adpted from (Carr et al., 2013)” and Teifi& Gronwen in Wales.

Then h_j can be calculated by,

$$H = (R^T R)^{-1} R^T Q \qquad (19)$$

In the calibration of the LVGFM method, the ordinary least squares (OLS) method was used to estimate the discrete weighting function ordinates (B_j). Then, the soil moisture state (z_i) was calculated through the SLM rainfall-runoff model outputs. Because varying gain factor (G_i) has a linear relation with the soil moisture state, it can be inferred that SLM acts as an auxiliary elementary model to estimate the gain factor.

Excel macros, Visual Basic, and MATLAB software packages were used to determine the parameters of these three selected models. The outputs of these methods were combined with the five combination methods (SAM, WAM, FSM, NNM, and ANFISM).

5.1. ANFIS combination method Calibration:

The parameters of NNM and FSM combination models were calibrated same as the Shamseldin et al., (1997) and Xiong et al., (2001), it has been clearly described in these papers and we just focus on ANFIS parameters calibration here. The data set was divided into two separate data sets, one for training and the other for testing. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the combination of rainfall-runoff models.

A crucial point in the rule base design is selecting the number of rules. It was determined experimentally, by developing various models and studying the rules and their results, which for three catchments, three rules was adopted. Just for Teifi catchment, results showed that application of fuzzy subtractive clustering algorithm with four clusters, the number of clusters determines the number of rules, can make a better adaptation with target outputs. In figure 6, the ANFIS rule base structure which was developed for Gronwen catchment can be seen. Each row corresponds to one rule, and each column corresponds to either an input variable or an output variable. The simple Gaussian membership function defined in equation (18) showed the best fit in the ANFIS model for all the four catchments. Finally, the hybrid-learning rule was used to train the model according to input/output data pairs. The ANFIS was implemented by using the MATLAB software package (MATLAB version R2010a with fuzzy logic toolbox).

$$f(x, \sigma, c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (20)$$

where x is one of the input data series to ANFIS which is originally one of the rainfall-runoff models output, and c and σ are the center and width of the fuzzy set, respectively.

6. RESULTS

As it can be seen in tables 3 and 4, for calibration and verification period, and for all the four catchments, the values of R^2 and RMSE for the adaptive neuro-fuzzy combination method are at the first rank. However, the differences of R^2 values for some of the watersheds, especially Teifi, are not significant. Another result that can be inferred from tables 3 and 4 is that neural network combination method is always at the second place. In the case of fuzzy system combination method, the results are disappointing especially in calibration period. For example, the R^2 value of fuzzy system combination method in the calibration period is around %71 and it ranks no. 6. However, the RMSE results are a little different from efficiency index for fuzzy system combination method, and its rank in three catchments is 3 and in one catchment is 4 in verification period.

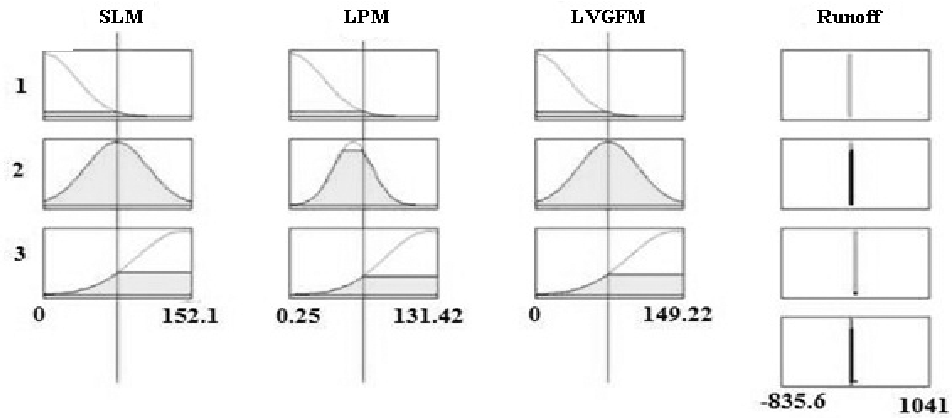

Figure 6. The ANFIS rule base structure developed for Gronwen catchment.

Table 3. The R^2 efficiency results on calibration and verification period

Model	R^2 (rank)%			
	Nfcc	Sfcc	Teifi	Gronwen
Calibration Period				
SLM	66.20 (7)	70.94 (7)	77.71 (5)	70.90 (4)
LPM	74.80 (4)	84.10 (4)	74.85 (7)	52.75 (7)
LVGFM	62.34 (8)	67.42 (8)	68.02 (8)	49.83 (8)
SAM	71.11 (5)	78.21 (6)	76.94 (6)	62.75 (6)
WAM	76.63 (3)	84.76 (3)	82.33 (3)	71.29 (3)
FSM	70.98 (6)	78.25 (5)	77.59 (4)	68.94 (5)
NNM	84.08 (2)	85.02 (2)	85.62 (2)	74.82 (2)
ANFISM	91.59 (1)	88.70 (1)	86.58(1)	79.31 (1)
Verification Period				
SLM	59.74 (7)	66.70 (7)	79.95 (6)	67.29 (5)
LPM	69.40 (4)	70.37 (5)	78.47 (7)	61.50 (7)
LVGFM	56.64 (8)	65.67 (8)	72.22 (8)	61.22 (8)
SAM	64.23 (6)	69.30 (6)	80.78 (5)	66.88 (6)
WAM	70.38 (3)	70.55 (4)	85.57 (3)	67.63 (4)
FSM	69.31 (5)	70.64 (3)	81.36 (4)	70.14 (3)
NNM	72.76 (2)	71.09 (2)	87.19 (2)	71.02 (2)
ANFISM	84.03 (1)	71.09 (1)	88.99 (1)	75.59 (1)

Analysis of the tables indicates that, the weighted average combination method (WAM) has shown good results, and in the calibration period, it always ranks no. 3 and in verification period is in third or fourth ranks. Also, the simple average combination method (SAM) performance is inferior to those of the other combination methods for all the four catchments.

The main goal of this study is to examine the combination methods in simulating runoff and flood events. So, we decided to compare the performance of the best rainfall-runoff model and NNM, FSM, and ANFISM combination models in simulating the maximum runoff event of each station in calibration period (Figures 7-10). As it can be seen in these figures, ANFISM has been simulated the maximum runoff superior than the other methods significantly. This superiority confirms the results in tables 3 and 4. These figures also demonstrate that NNM, FSM, and individual rainfall-runoff model (SLM for Teifi and Gronwen, and LPM for NFLO and SFLO) are the next best models after ANFISM.

The Accurate estimations of flood peak timing by ANFISM simulations in three catchments and one day delay for Gronwen catchment is also noticeable. Once the performance of ANFISM in combining the outputs of rainfall-runoff models was promising based on the evaluation criteria and simulating the flood events in the calibration period, we wanted to examine how well the ANFIS simulated the distribution of runoff in four watersheds in validation period.

Table 4. The RMSE efficiency results on calibration and verification period

Model	RMSE (rank)			
	Nfcc	Sfcc	Teifi	Gronwen
Calibration Period				
SLM	3.96 (7)	5.39 (7)	13.13 (4)	10.43 (4)
LPM	3.43 (4)	3.99 (4)	13.95 (7)	13.30 (7)
LVGFM	4.19 (8)	5.71 (8)	15.73 (8)	13.70 (8)
SAM	3.67 (6)	4.67 (6)	13.36 (6)	11.81 (6)
WAM	3.29 (3)	3.90 (3)	11.69 (3)	10.36 (3)
FSM	3.46 (5)	4.67 (5)	13.17 (5)	10.78 (5)
NNM	2.72 (2)	3.87 (2)	10.55 (2)	9.71 (2)
ANFISM	1.98 (1)	3.36 (1)	10.19 (1)	8.80 (1)
Verification Period				
SLM	4.58 (7)	7.40 (7)	13.99 (6)	13.85 (5)
LPM	3.99 (5)	6.98 (5)	14.49 (7)	15.03 (7)
LVGFM	4.75 (8)	7.51 (8)	16.47 (8)	15.08 (8)
SAM	4.32 (6)	7.10 (6)	13.69 (5)	13.94 (6)
WAM	3.93 (4)	6.96 (4)	11.87 (3)	13.78 (4)
FSM	3.78 (3)	6.95 (3)	13.49 (4)	13.24 (3)
NNM	3.77 (2)	6.89 (2)	11.18 (2)	13.04 (2)
ANFISM	2.88 (1)	6.89 (1)	10.36 (1)	11.97 (1)

The Q-Q plots of three rainfall-runoff models and five combination methods were compared (Figures 11-14). Here, the superiority of ANFISM over the other methods is considerable, especially in Gronwen, Teifi, and NFLO watersheds.

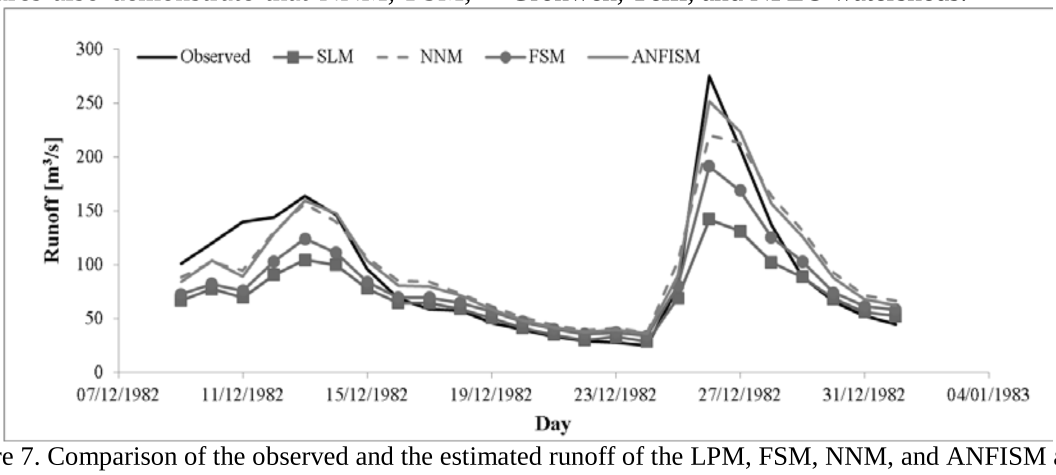

Figure 7. Comparison of the observed and the estimated runoff of the LPM, FSM, NNM, and ANFISM at the Teifi catchment

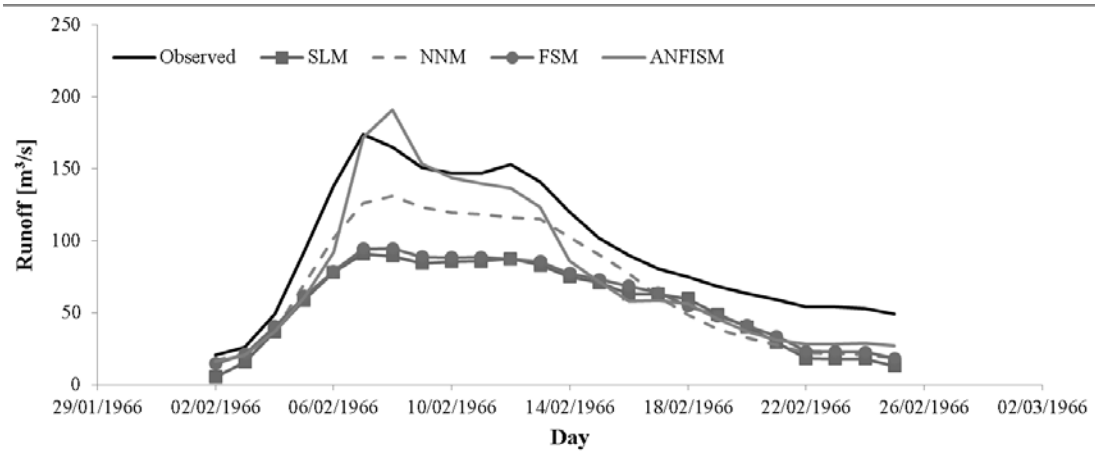

Figure 8. Comparison of the observed and the estimated runoff of the LPM, FSM, NNM, and ANFISM at the Gronwen catchment

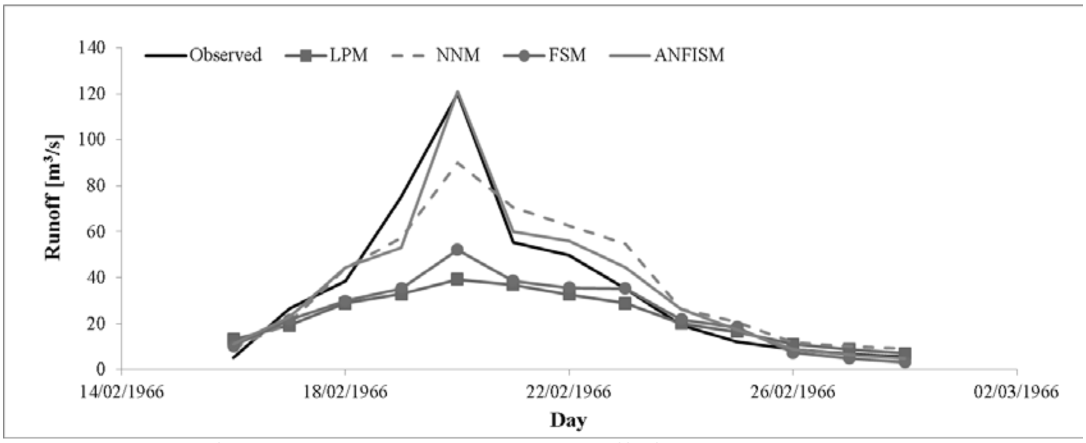

Figure 9. Comparison of the observed and the estimated runoff of the LPM, FSM, NNM, and ANFISM at the Nfcc catchment

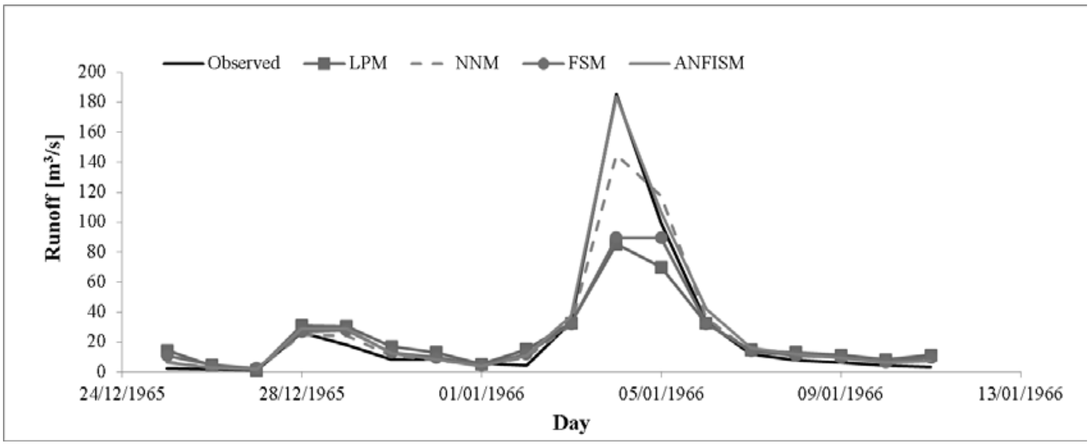

Figure 10. Comparison of the observed and the estimated runoff of the LPM, FSM, NNM, and ANFISM at the Sfcc catchment

As it can be noted, the other methods underestimate the flood events, while ANFISM is the only method that can simulate flood events reasonably. From these figures (Figures 11-14), it can be concluded that ANFIS is a reliable method to be implemented in flood forecasting systems. However, the evaluation criteria differences of NNM and ANFISM was insignificant for some cases, but it is clear that neural network model fails to simulate extreme runoff.

The reason of such an occurrence can be the inability of neural networks to extrapolate the data which is needed for some of the cases for the validation period. When extrapolation is needed beyond the limits of the training data, fuzzy logic approach enhances the generalization capability of a neural network by providing more reliable outputs (Matreata, 2006).

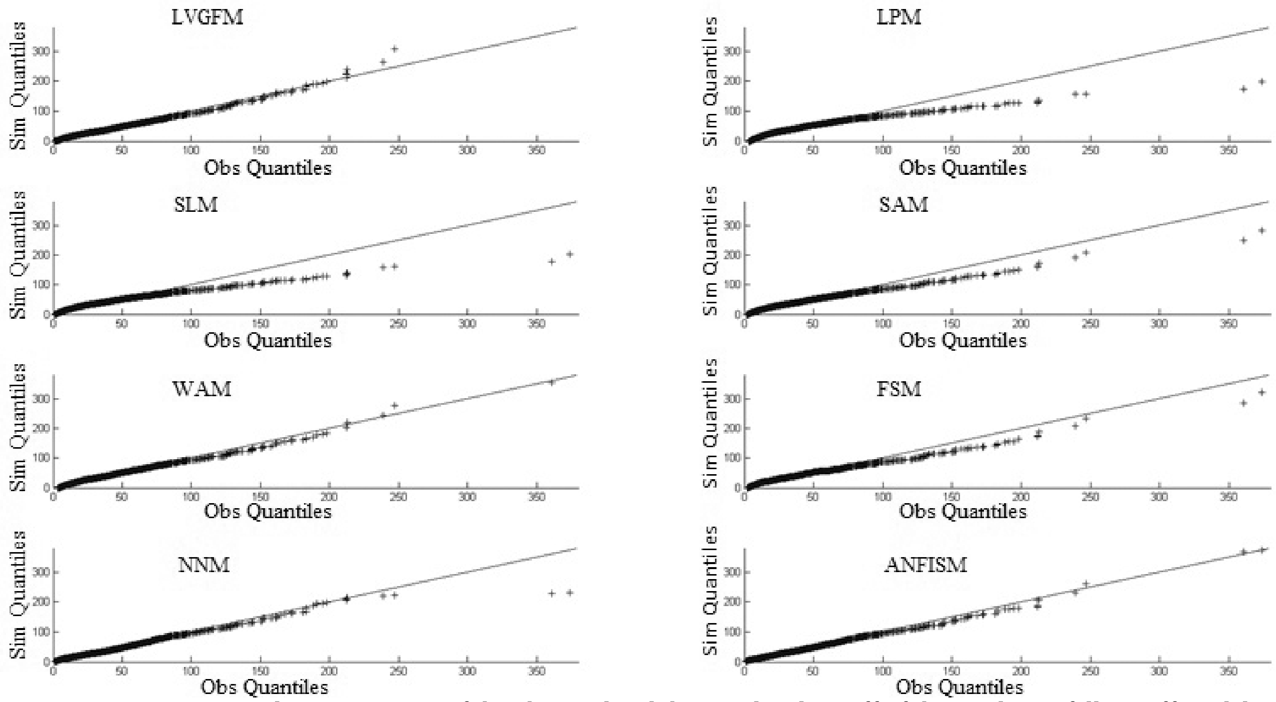

Figure 11. Q-Q plot Comparison of the observed and the simulated runoff of the single rainfall-runoff models and the combination methods at the Teifi catchment.

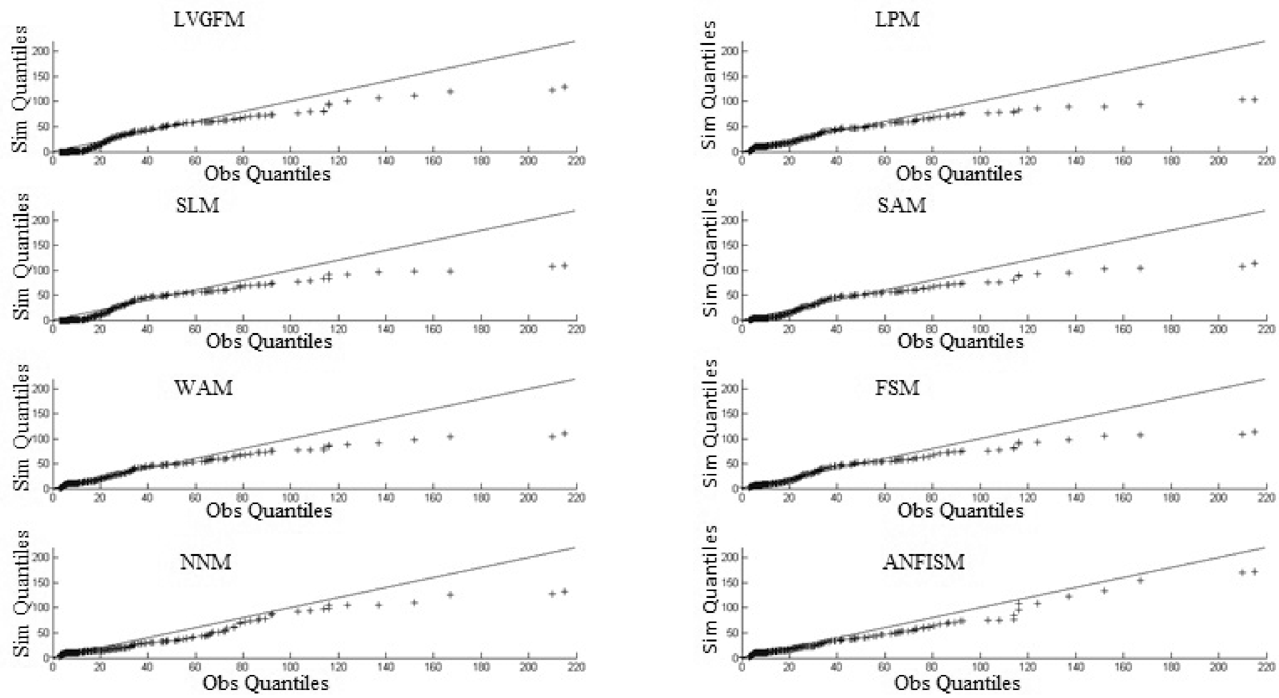

Figure 12. Q-Q plot Comparison of the observed and the simulated runoff of the single rainfall-runoff models and the combination methods at the Gronwen catchment

7. DISCUSSIONS AND CONCLUSIONS

Considerable research has been carried out to have a reliable flood forecasting system and a large number of rainfall-runoff models have been proposed. Shamseldin et al., (1997) and Zhang et al., (2009) indicated the advantages of combining the forecasts of rainfall-runoff models.

Georgakakos et al., (2004) attributed the superior skill of the combination methods to the fact that rainfall-runoff model structural uncertainty is accounted for in the combination approach. They suggested that forecast combination of rainfall-runoff models should be considered as an operational forecasting tool. The results of this study, not only supported their findings, but also, introduced the ANFIS combination method which performed better than the other combination methods (SAM, WAM, FSM, and NNM) and the best individual rainfall-runoff model.

Furthermore, ANFIS combination method provided improved flood estimates that can be used by engineers and hydrologists. So, they can apply a combination method like ANFIS in modeling complicated and significant phenomena like flood and drought events with more reliability. No numerous parameters calibration requirement and resolving overparameterization effects of an immense hydrologic model are the other advantages of developing a rainfall-runoff combination method.

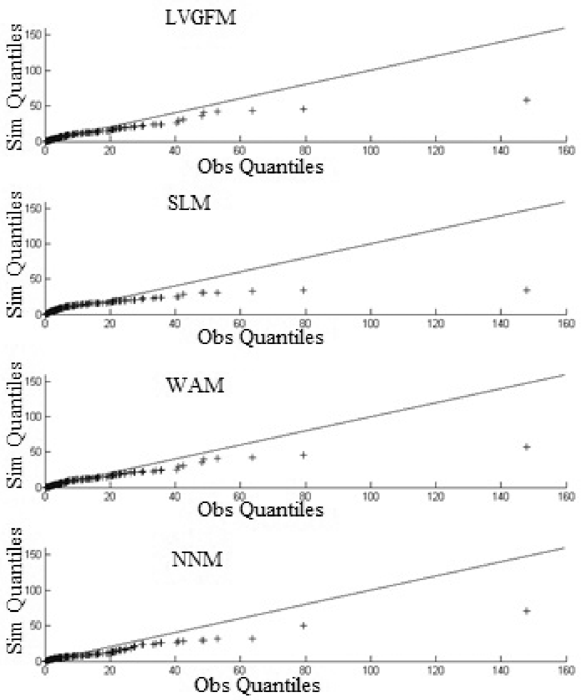

Figure 13. Q-Q plot Comparison of the observed and the simulated runoff of the single rainfall-runoff models and the combination methods at the Nfcc catchment.

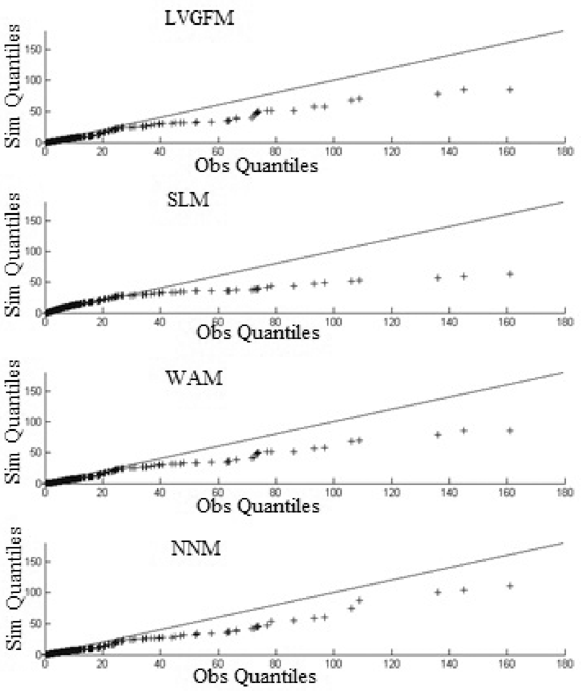

Figure 14. Q-Q plot comparison of the observed and the simulated runoff of the single rainfall-runoff models and the combination methods at the Sfcc catchment

As it was discussed by Matreata (2006), when extrapolation is needed beyond the limits of the training data, fuzzy logic approach enhances the generalization capability of a neural network by providing more reliable outputs which can be an advantage in flood forecasting systems compared with neural networks combination methods.

As it was concluded by Zhang et al., (2009), the performance of single rainfall-runoff models has the apparent influence on the performance of combination methods. Underestimation of flood events by single rainfall-runoff models would cause the underestimation by combination methods as it was observed in figures 11-14. So, using more comprehensive rainfall-runoff models could possibly enhance the accuracy of combination methods. This can especially help at the large river basins where using only rainfall as an input to a black-box model would not be a reliable approach.

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REFERENCES

Ahsan, M. & O'Connor, K.M., 1994 *A Simple Non-Linear Rainfall-Runoff Model with a Variable Gain Factor*. J. Hydrology, 155 (1-2), 151-183.

ASCE Task Committee 2000 *Artificial Neural Networks in Hydrology I: Preliminary Concepts*. J. Hydrologic Eng., ASCE, 5(2), 115-123.

Beven, K., 1989 *Changing ideas in hydrology - The case of physically-based models*. J. Hydrology, 105 (1-2), 157-172.

Beven, K., 2001 *Rainfall-runoff Modelling*: The Primer. John Wiley and Sons, Chichester, UK. Pg. 1-23.

Box, G.E.P. & Jenkins, G., 1970 *Time Series Analysis, Forecasting and Control*. Holden-Day, San Francisco. pp. 137-187.

Buzas, K., 2001 *Use of Fuzzy Method to Estimate River Nutrient Loads from Scarce Observation,* Water Science and Technology, 43(7), 257-264.

Carr, A.E., Loague, K. & VanderKwaak, J.E., 2013. *Hydrologic-response simulations for the North Fork of Caspar Creek: second-growth, clear-cut, new-growth, and cumulative watershed effect scenarios*. Hydrological Processes, DOI:10.1002/hyp.9697.

Chang, F.J. & Chang, Y.T., 2006. *Adaptive Neuro-Fuzzy Inference System for Prediction of Water Level in Reservoir.* Adv. in Water Res., 29, 1-10.

Coulibaly, P., Hache, M., Fortin, V. & Bobee, B., 2005 *Improving Daily Reservoir Inflow Forecasts with Model Combination*. J. Hydrol. Eng., ASCE, 10(2), 91-99.

Dastorani, M.T., Moghadamnia, A., Piri, J. & Rico-Ramirez, M., 2010. *Application of ANN and ANFIS models for reconstructing missing flow data*. Environmental Monitoring and Assessment, 166(1-4), pp. 421-434.

De Vos, N.J. & Rientjes, T.H.M., 2005 *Constraints of Artificial Neural Networks for Rainfall-Runoff Modeling: Trade Offs in Hydrological State Representation and Model Evaluation.* Hydrol. Earth Syst. Sci. Discuss., 2, 365-415.

Du, J., Xie, S., Xu, Y., Xu, C.Y. & Singh, V.P., 2007 *Development and Testing of a Simple Physically-Based Distributed Rainfall-Runoff Simulation in Humid Forested Basins*. J. Hydrology, 336, 334-346.

El-Shafie, A., Jaafer, O. & Seyed, A., 2011 *Adaptive neuro-fuzzy inference system based model for rainfall forecasting in Klang River, Malaysia*. International Journal of Physical Sciences, 6(12), pp. 2875-2888.

Ewen, J., O'Donnell, G., Burton, A. & O'Donnell, E., 2006 *Errors and Uncertainty in Physically Based Rainfall-Runoff Modeling of Catchment Change Eeffects.* J. Hydrology, 330, 641-650.

Fayaed, S.S., El-Shafie, A. & Jaafar, O., 2011. *Adaptive neuro-fuzzy inference system-based model for elevation-surface area-storage interrelationships.* Neural Computing and Applications, pp. 1-12. doi:10.1007/s00521-011-0790-4

Fernando, D.A.K., Shamseldin, A.Y. & Abrahart, R.J., 2009 *Using gene expression programming to develop a combined runoff estimate model from conventional rainfall-runoff model outputs. 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation*: Interfacing Modelling and Simulation with Mathematical and Computational Sciences, Proceedings, pp. 748-754.

Firat, M. & Gungor, M., 2007. *River Flow Estimation Using Adaptive Neuro Fuzzy Inference System*. Mathematics and Computers in Simulation, 75(3-4), 87-96.

Georgakakos, K.P., Seo, D-J., Gupta, H., Schaake, J. & Butts, M.B., 2004 *Towards the characterization of streamflow simulation uncertainty through multimodel ensembles.* Journal of Hydrology, 298 (1-4), pp. 222-241.

Granger, C.W.J. & Ramanathan, R., 1984 *Improved Methods of Combining Forecasts*. J. Forecasting, 3 (2), 197-204.

Guangtao, F.U., 2008 *A Fuzzy Optimization Method for Multicriteria Decision Making: An Application to Reservoir Flood Control Operation.* Expert Systems with Applications, 34(1), 145-149.

Jain, A. & Prasad Indurthy, S.K.V., 2003 *Comparative Analysis of Event-Based Rainfall-Runoff Modeling Techniques- Deterministic, Statistical, and Artificial Neural Networks.* J. Hydrol. Eng., ASCE, 8(2), 93-98.

Jang, J.S.R., 1993. *ANFIS: Adaptive-Network-Based Fuzzy Inference System*. IEEE Trans. System, Man, Cybernet, 23(3), 665-685.

Jonsdottir, H., Madsen, H. & Palsson, O.P., 2006 *Parameter Estimation in Stochastic Rainfall-Runoff Models.* J. Hydrology, 326, 379-393.

Kachroo, R.K. & Liang, G.C., 1992 *River Flow Forecasting. Part 2. Algebraic Development of Linear Modelling Techniques.* J. Hydrology, 133(1-2), 17-40.

Keskin, M.E., Taylan, D. & Terzi, O., 2006 *Adaptive Neural-Based Fuzzy Inference System (ANFIS) Approach for Modelling Hydrological Time Series*. Hydrol. Sci. J., 51(4), 588-598.

Kim, S.H. & Delleur, J.W., 2001 *Stochastic Structures between Quantity and Quality Responses of Rainfall-Runoff at an Upland Agricultural Watershed.* Water Science and Technology, 44(7), 91-104.

Kisi, O., Karahan, M.E. & Sen, Z., 2006. *River Suspended Sediment Modelling Using a Fuzzy Logic Approach.* Hydrological Processes, 20(20), 4351-4362.

Lee, H., McIntyre. N., Wheater, H. & Young, A., 2005 *Selection of Conceptual Models for Regionalization of the Rainfall-Runoff Relationship.* J. Hydrology, 312, 125-147.

Li, R.Z., Shigeki, M., Hong, T.Q. & Qian, J.Z., 2007 *Fuzzy Model for Two-Dimensional River Water Quality Simulation Under Sudden Pollutants Discharged*. J. Hydrodynamics, 19(4), 434-441.

Liang, Z., Dai, R., Wang, J., Yu, Z., 2010 *Study on forecast combination of different hydrological models by Bayesian model averaging. Shuili Fadian Xuebao*. Journal of Hydroelectric Engineering, 29(2), pp. 114-118.

Mahabir, C., Hicks, F.E. & Fayek, A.R., 2003 *Application of Fuzzy Logic to Forecast Seasonal Runoff*. Hydrological Processes, 17, 3749-3762.

Matreata, M., 2006 *Overview of the artificial neural networks and fuzzy logic applications in operational hydrological forecasting systems*. Proceedings of the conference Balwois, Ohrid, Republic of Macedonia, 23–26 May, 2006. DOI=10.1.1.138.7413.

McIntyre, N., Al-Qurashi, A., Wheater, H., 2007 *Regression Analysis of Rainfall-Runoff Data from an Arid Catchment in Oman*. Hydrological Sciences J., 52(6), 1103-1118.

McLeod, A.I., Noakes, D.J., Hipel, K.W. & Thompstone, R.M., 1987 *Combining Hydrologic Forecast.* J. Water Res. Plan. Manage., ASCE, 113 (1), 29-41.

Nash, J.E. & Barsi, B.I., 1983 *A Hybrid Model for Flow Forecasting on Large Catchments.* J. Hydrology, 65 (1-3), 125-137.

Nash, J.E. & Foley, J.J., 1982 *Linear Models of Rainfall-Runoff Systems. Rainfall-Runoff Relationship*. Proceedings of the International Symposium on Rainfall Runoff Modeling, Mississippi State University, USA. Water Resources Publications, 51-66.

Nash, J.E. & Sutcliffe, J.V., 1970 *River Flow Forecasting trough Conceptual Models- PT 1*. J. Hydrology, 10 (3), 282-290.

Nedjah, N. & Mourelle, L.D.M., 2005 *Fuzzy systems engineering: Theory and Practice*. Springer, Berlin. Pg. 53-80.

Niedzielski, T., 2007 *A Data-Based Regional Scale Autoregressive Rainfall-Runoff Model: A Study from the Odra River.* Stochastic Environmental Research and Risk Assessment, 21(6), 649-664.

Ozelkan, E.C. & Duckstein, L., 2001 *Fuzzy Conceptual Rainfall-Runoff Models.* J. Hydrology, 253 (1-4), 41-68.

Pan, T.Y., Wang, R.Y., Lai, J.S., 2007 *A Deterministic Linearized Recurrent Neural Network for Recognizing the Transition of Rainfall-Runoff Processes.* Adv. in Water Res., 30, 1797-1814.

Shahin, M.A., Jaksa, M.B. & Maier, H.R., 2008 *State of the art of artificial neural networks in geotechnical engineering.* Electronic Journal of Geotechnical Engineering, pp. 1-26.

Shamseldin, A.Y. & O'Connor, K.M., 1999 *A Real-Time Combining Method for the Outputs of Different Rainfall-Runoff Models.* Hydrol. Sci. J., 44(6), 895-912.

Shamseldin, A.Y., O'Connor, K.M. & Liang, G.C., 1997 *Methods for Combining the Outputs of Different Rainfall-Runoff Models*. J. Hydrology, 197, 203-229.

Shamseldin, A.Y., O'Connor, K.M., Nasr, A.E., 2007. *A comparative study of three neural network forecast combination methods for simulated river flows of different rainfall-runoff models*. Hydrol. Sci. J., 52 (5), 898-916

Tareghian, R. & Kashefipour, S.M., 2007 *Application of Fuzzy Systems and Artificial Neural Networks for Flood Forecasting.* J. Applied Sciences, 7(22), 3451-3459.

Tayfur, G. & Singh, V.P., 2006 *Ann and Fuzzy Logic Models for Simulating Event-Based Rainfall-Runoff.”* J. Hydrologic Eng., ASCE, 132 (12), 1321-1330.

Xiong, L., Shamseldin, A.Y. & O'Connor, K.M., 2001 *A Non-Linear Combination of the Forecasts of Rainfall-Runoff Models by the First Order Takagi-Sugeno Fuzzy System*. J. Hydrology, 245, 196-217.

Zadeh, L.A., 1965 *Fuzzy Sets. Information Control*, 8, 338-353.

Zhang, L., Zhao, W., He, Z., Liu, H., 2009 *Application of the Takagi-Sugeno Fuzzy System for Combination Forecasting of River Flow in Semiarid Mountain Regions*. Hydrological Processes, 23(10), 1430-1436.

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