DEVELOPMENT AND EVALUATION OF AN ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR THE CALCULATION OF SOIL WATER RECHARGE IN A WATERSHED

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Abstract

Modeling of groundwater recharge is one of the most important topics in hydrology due to its essential application to water resources management. In this study, an Adaptive Neuro Fuzzy Inference System (ANFIS) method is used to simulate groundwater recharge for watersheds. In-situ observational datasets for temperature, precipitation, evapotranspiration, (ET_o) and groundwater recharge of the Lake Karla, Thessaly, Greece watershed were taken into consideration for the present study. The datasets consisted of monthly average values of the last almost 50 years, where 70% of the values used for learning with the rest for the testing phase. The testing was performed under a set of different membership functions without expert's knowledge acquisition and with the support of a five-layer neural network. Experimental verification shows that, the 3-3-3 combination under the trapezoid membership function with the hybrid neural network support and the 2-2-2 combination under the g-bell membership function with the same neural network support perform the best among all combinations with RMSE 4.78881 and 4.12944 giving on average 5% deviation from the observed values.

Keywords: Groundwater Recharge, Neuro Fuzzy Inference

Introduction

Soil water content is a key parameter that controls several hydrological processes and provides valuable information for water resources planning and management. Soil water modeling is very important for hydrology, weather and climate studies, water resource management, reliable irrigation design, and determining contaminants and nutrients' fate and transport. For a watershed, the groundwater recharge or deep drainage or deep percolation is the hydrologic process where water moves downward from surface water to groundwater. This process usually occurs in the zone below the level of the plant roots and is often expressed as a flux to the water table surface (Allison, 1978). Thus, the accurate estimation of groundwater recharge has an importance for water resource engineering problems such as soil water balance, irrigation systems and water supply for cultivation.

Furthermore, groundwater recharge is a process which is highly affected by a variety of non-linear factors like rainfall characteristics and overall precipitation, watershed morphology, evapotranspiration occurred in the area, soil moisture, etc. However, any effort to model the relationship between the groundwater recharge and the aforementioned factors would be confronted with difficulties including being highly non-linear, time-varying, spatially distributed, and stochastic. In addition, the deficiencies in data like missing data, noisy data, and in some cases having insufficient data present a major problem in groundwater recharge modeling.

In the past decades, several soft computing techniques have been applied in a number of diverse fields including system modeling, fault diagnosis and control, pattern recognition, financial forecasting and water resources. These techniques are known for their efficiency in dealing with complicated problems, with only sets of operational data available. However, the application of soft computing techniques to groundwater recharge modeling and the modeling of several hydrological processes in general is limited in the literature. To the best of our knowledge there are just few publications that are mostly related to the rainfall-runoff, the forecasting of inflows into a reservoir and some works that are dealing with the estimation and forecasting of the evapotranspiration factor in a watershed. From this point of view, the application of soft computing techniques for the forecasting of groundwater recharge initiates a new research branch for the groundwater modeling.

In this work we develop an Adaptive Network Fuzzy Inference System (ANFIS) for the forecasting of groundwater recharge. The modeling is based on using three input time series namely: temperature, precipitation and evapotranspiration. The output is a time series of the groundwater recharge. The system we develop is based on time series of monthly values since the decade of 1960's up to date and refers to the Lake Karla watershed

in Thessaly Greece. For this time period, we have also collected observational data regarding the groundwater recharge taken from several observation wells located in the area against which, we compare our ANFIS simulation.

In the following sections, we describe: a short yet compact literature review on the fuzzy inference systems, (FIS) and the applications of FIS into hydrological modeling, a description of the region under study, the development and the specifics of the ANFIS and a discussion of the results produced. Finally, conclusions and future challenges are drawn.

Literature Review

Most of the soft computing methodologies that deal with hydrological processes mainly focus on the prediction of rainfall-runoff and the evapotranspiration. The prediction of the rainfall-runoff is closely depended on factors such as the precipitation, evaporation, transpiration, interception, infiltration, stream flow and of course the variability in time and space of the above. However, the rainfall-runoff is practically contributes mainly to deep percolation especially for basins and watersheds with impermeable boundaries.

Research that deals with this prediction is divided in the categories of Artificial Neural Networks (ANN), Genetic Algorithms and Fuzzy Logic. However we concentrate only in the Fuzzy Logic methodology since our work is closely related to that category.

The work in (Talei et al., 2010) used an ANFIS for event-based rainfall-runoff modelling. The results of the ANFIS were compared with an established physical-based model. The study showed that ANFIS is comparable to the physical model and is found to give a better peak flow estimation compared to the physical model. Also (Dorum et al., 2010) compared the predictions of rainfall-runoff data using ANN and ANIFS methods. For this comparison they used a multi regression. This study showed that ANN and ANIFS models can be used in determination of rainfall runoff relationships of basins except peak situations.

The work by (Gerner, A., 2013) mainly focuses on the uncertainty regarding the potential, albeit unknown extent of groundwater basins based on continuous surfaces which represent the degree of membership to a distinct geographical entity (termed as fuzzy regions). The proposed strategy was applied on the large scale in an arid karst mountain range in northern Oman. The ANFIS methodology applied was in good agreement with the results of other conceptual hydrologic models used and was confirmed by the plausibility of average recharge rates for distinct response units and seasons.

Also (Umamaheswari and Kalamani, 2014) employed an ANFIS approach to observe its applicability on prediction and forecasting of

monthly groundwater level fluctuation in the study area (Amaravathi River Minor Basin). Their proposed model was the best fit by the hybrid technique with 6:3:3 membership functions with their forecasted model performance to exactly replicate the current situation of the groundwater system.

Finally, in the most recent research work, (Maiti and Tiwari, 2014) examined the comparative merits and demerits of ANN, Bayesian ANN and ANFIS in the predictive modeling of groundwater level fluctuations. Initially they carried out a sensitivity analysis based on an automatic relevance determination scheme to examine the relative influence of each of the hydro-meteorological attributes on groundwater level fluctuations. Then, the 3 techniques were applied to model the groundwater level fluctuation time series of six wells from a hard rock area of Dindigul in Southern India. They compared the 3 models using standard quantitative statistical measures such as Root Mean Square Error, (RMSE) and Pearson's correlation coefficient (*R*). Based on the above analyses, it was found that the ANFIS model performed better in modeling noise-free data than the other two models.

Study Area

We are dealing with the hydrological processing of the surrounding watershed of Lake Karla in Thessaly, Greece. The natural basin of Lake Karla was initially extended in an area of 1,663 km^2 but after the construction of complimentary works, the drainage area of the restored lake Karla will be 1171 km^2 (Figure 1-Left) (Loukas et al., 2007).
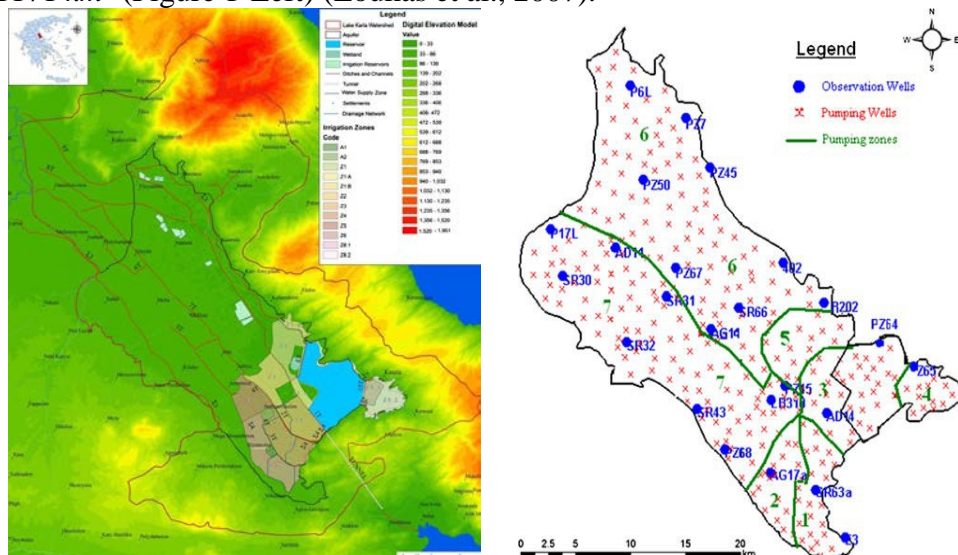

Fig. 1 Left) Lake Karla basin map indicating the underlying aquifer and the reservoir. Right) Aquifer map with pumping wells, zones and observation wells.

The region is characterized by its continental Mediterranean climate and there is a noticeable fluctuation of temperature between winter and summer time. The average temperature is 16-17° C and the mean annual relative humidity is 67%-72%. Snowfall is usually on the mountains during winter when significant snow peaks develop.

The waters of the region are used primarily for irrigation. Unfortunately, the water balance of the watershed is disturbed and it keeps deteriorating due to the overexploitation of the groundwater system resulting into the degradation of the available water resources. The phreatic aquifer of the lake has been simulated by the Modflow numerical model, (Harbaugh et al., 2000). The region has been discretized into an orthogonal grid of 40.000 cells, with a grid spacing of 200m X 197m. The resulting network has covered a region of about 500 km^2. To the west a (not so strong) hydraulic contact with the adjacent aquifer has been established and simulated with the General Head Boundary while the eastern boundary, consisting of schist was considered impermeable. The primary surface inflow of the model was the surface recharge. The study area was divided into 7 pumping zones, as is shown in (Figure 1-Right).

Adaptive Neuro Fuzzy Inference Systems

A fuzzy inference system (FIS) is an inference mapping that provides an intuition for the relationship between a series of input and output sets. This mapping from a given input to an output using fuzzy logic is called Fuzzy Inference (Adriaenssens et al., 2004). These systems have proved to work better when the input and output sets are time series data of the same time step. The FIS uses fuzzy logic principles to establish the input-output relationship through a rule based inference engine that consists of: (a) a rule-base, containing fuzzy if–then rules, (b) a data-base, defining the membership functions (MF) and (c) an inference system, combining the fuzzy rules and producing the system results (Sen, 2001). There are two types of popular FIS, the Takagi–Sugeno FIS, (Takagi and Sugeno, 1985) and the Mamdani FIS (Jang et al., 1997). The difference between the two approaches is the definition of the consequent parameters in the network. The FIS used in this study is a Takagi and Sugeno type FIS in which the rule base is constructed from the input–output pairs and it consists of five layers as seen in Figure 2: (L1) Input fuzzification, (L2) Fuzzy set database construction, (L3) Fuzzy rule base construction, (L4) Decision making and (L5) Output defuzzification.
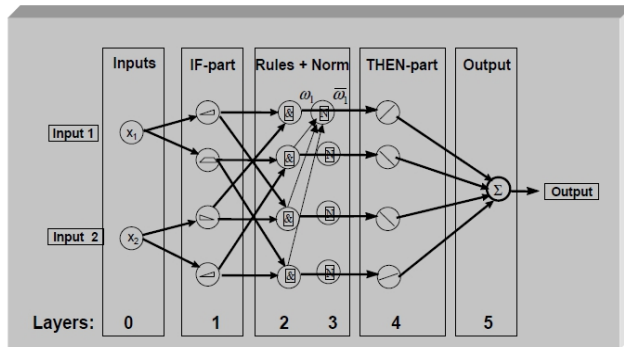
Fig. 2 Adaptive neuro-fuzzy inference system structure (Khoshnevisan et al. 2014)

In Layer 1, every node i is an adaptive node with a node function, given in eq. (1):

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \tag{1}$$

where x indicates the input to node i, A_i represents the linguistic label associated with this node function, and $O_{1,i}$ is the membership function of A_i that specifies the degree to which the given x satisfies A_i. Regarding all other input y, the node functions have exactly the same behavior with the function family as x, with the condition that they belong to the same layer. In Layer 2, every node is a fixed node and acts as a simple multiplier. The outputs of these nodes are given by eq. (2):

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad for\ i = 1,2 \tag{2}$$

which are the so-called firing strengths of the rules.

Every node, in Layer 3, is an adaptive node indicated as N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths. Eq. (3) shows how to obtain the output of this layer:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{3}$$

Each node, in Layer 4, is an adaptive node with a function given by eq. (4):

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{4}$$

where $\overline{w_i}$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ are referred to as consequent parameters. Finally, the single node, in Layer 5, is a fixed node indicated as $\sum$ (sum) that computes the overall output as the sum of all incoming inputs:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

To construct an ANFIS from a given input/output data set, we first construct the FIS whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method (Singh et al., 2012). Learning using the

neuro-adaptive method works similarly to that of neural networks as for the procedure to learn information about a data set. In other words, ANFIS, which is a combination of ANN and FIS, has the benefits of the two models (Azadeh et al., 2011). Propagation and hybrid are two learning methods which are generally applied in ANFIS to clearly describe the relationship between input and output (Khoshnevisan et al. 2014). Hybrid learning, which is a combination of gradient decent method and least squares approach, can decrease the complexity of the algorithm and simultaneously increase the learning efficiency. The parameters associated with membership functions will change through the learning process using a gradient vector that facilitates in this recalculation. So every time the gradient vector is obtained, an optimization procedure can be performed to adjust parameters in order to reduce errors.

ANFIS application in predicting groundwater recharge
        For our simulation we used the Matlab 2014(b)-ANFIS tool named ANFIS-Editor. The tool is designed to utilize different variables including a normalization method, trial step quantity and various data classification methods to achieve the minimum error between predicted values and real data. The number and type of membership functions, (MF), the type of output MF, the optimization method (hybrid or back propagation) and the number of epochs are five important adjustments in ANFIS to reach the most effective model with minimum errors. Figure 3 summarizes the types of membership functions used in our simulation. Our primary goal was to find the effect of these adjustments and their subdivisions in different combinations in order to develop these ANFIS models and compare the results. For this purpose, all possible combinations of these adjustments are applied to the same sets of training and testing data. For the aforementioned reasons, we included in our experiment four data monthly time series of 434 values with each one spanning almost the last 50 years of observations, namely: temperature, precipitation, evapotranspiration and groundwater recharge. The first three are used as the input data whereas the groundwater recharge is the one that our system predicts. Out of the 434 values, the first 303 values are used for training and the rest 131 for testing and forecasting.
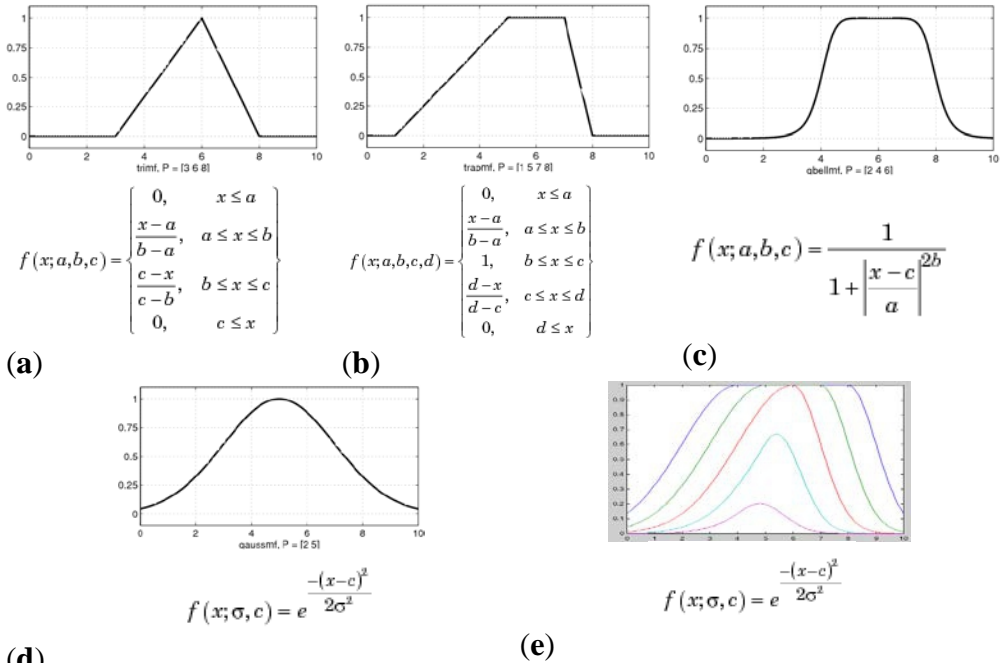
$$f(x;a,b,c)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases}$$

$$f(x;a,b,c,d)=\begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

$$f(x;a,b,c)=\dfrac{1}{1+\left|\dfrac{x-c}{a}\right|^{2b}}$$

(**a**)   (**b**)   (**c**)

$$f(x;\sigma,c)=e^{\dfrac{-(x-c)^2}{2\sigma^2}}$$

$$f(x;\sigma,c)=e^{\dfrac{-(x-c)^2}{2\sigma^2}}$$

(**d**)   (**e**)

Fig. 3 Membership functions used in the ANFIS: (a) trimf, (b) trapmf, (c) gbelmf, (d) gaussmf and (e) gauss2mf.

The same split of the data set was used for every combination of membership function and function type. Figure 4 shows the loading of training data and the basic configuration of the ANFIS-Editor module.
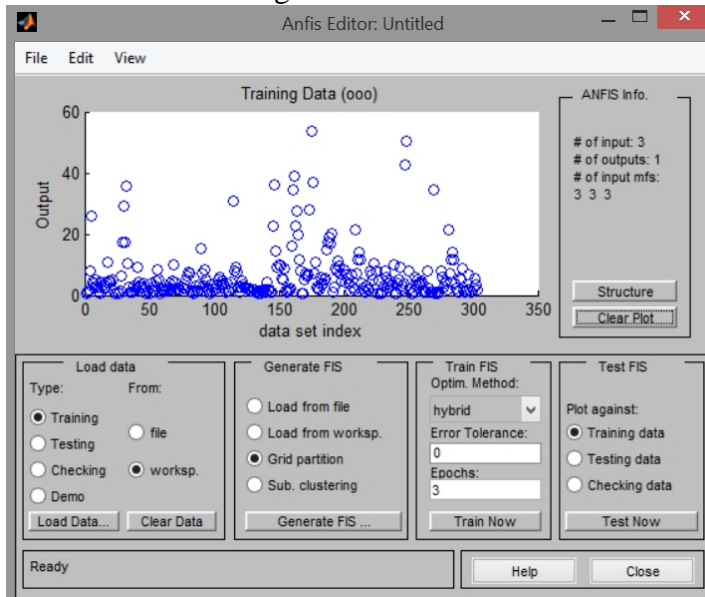

Fig. 4 Training phase in anfisedit and selection of the fuzzy inference system.

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The Takagi & Sugeno fuzzy inference system contains an inference engine in which the conclusion of a fuzzy rule comprises a weighted linear combination of the crisp inputs rather than a fuzzy set (Takagi and Sugeno, 1985). The system has the following structure:

$$IF \quad x \ is \quad A \quad and \quad y \ is \quad B \quad THEN \quad f = px + qy + r \qquad (6)$$

where p, q, and r are constant parameters. The model is suitable for approximating a large class of non-linear systems. For our case, the fuzzy rules are purely constructed from data without any expert's knowledge acquisition. In this case, the fuzzy rules are designated a priori and the parameters of the membership functions are adapted during the learning process from input to output data using a hybrid neural network. The neural net defines the shape of the membership functions of the premises. Figure 5-Left shows an example of the unsupervised construction of fuzzy rules and Figure 5-Right the corresponding neural network that participates in this construction.
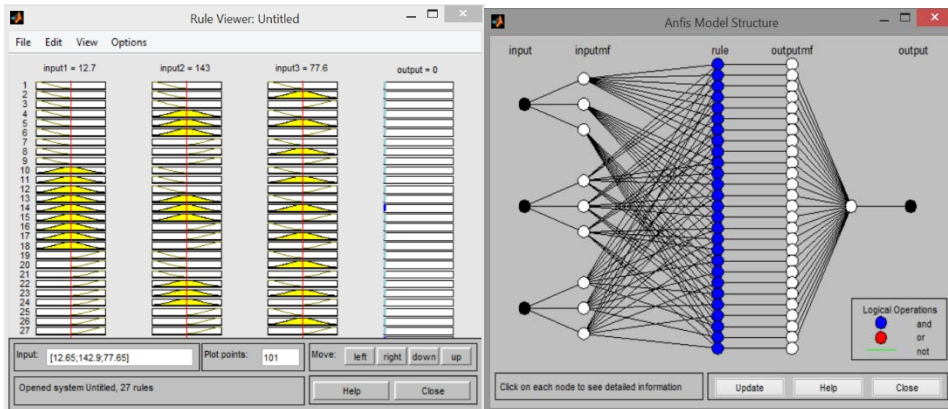

Fig. 5 Left) Fuzzy rule viewer for the case of the 3-3-3 trapmf membership function. Right) The corresponding 5-layer neural network that participates in the construction of the fuzzy rules.

For the learning/training part, the system uses two passes in the hybrid learning procedure. In the forward pass of the hybrid-learning algorithm, the system forces the functional signals of the neural network to go forward till layer 4. At this point, the consequent parameters are identified by the least-squares estimate. We then move to the backward pass, where the error rates propagate backward and the premise parameters are updated by the gradient descent. In our case the parameters are fixed, for both combinations 3-3-3 and 2-2-2. Thus for both cases the overall output is expressed as a linear combination of the consequent parameters. Table 1 depicts all the results taken after running 5 simulations with the combination 3-3-3 and another 5 simulations with the combination 2-2-2.

TABLE 1									
Number of Membership Functions: 3-3-3 Linear							**Optimization: Hybrid/Back**		
MFT	**NN**	**NLP**	**NNLP**	**TNP**	**NTDP**	**NCDP**	**NFR**	**RMSE**	**MAPE**
trimf	78	108	27	135	303	131	27	133.41975	16.6720
trapmf	78	108	36	144	303	131	27	4.78881	2.10136
gbelmf	78	108	27	135	303	131	27	13.67616	3.05041
gaussmf	78	108	18	116	303	131	27	8.80895	2.26571
gauss2mf	78	108	36	144	303	131	27	6.85502	2.35748
Number of Membership Functions: 2-2-2 Linear							**Optimization: Hybrid/Back**		
	NN	**NLP**	**NNLP**	**TNP**	**NTDP**	**NCDP**	**NFR**	**RMSE**	**MAPE**
trimf	34	32	18	50	303	131	8	6.61821	7.01869
trapmf	34	32	24	56	303	131	8	6.95011	2.26861
gbelmf	34	32	18	50	303	131	8	4.12944	1.92513
gaussmf	34	32	12	44	303	131	8	4.69009	2.04586
gauss2mf	34	32	24	56	303	131	8	5.74805	2.17019
MFT= Membership Function Type **NN** = Number of Nodes **NLP** = Number of Linear Parameters **NNLP** = Number of Non-Linear Parameters **TNP** = Total Number of Parameters					**NTDP** = Number of Training Data Pairs **NCDP** = Number of Checking Data Pairs **NFR**= Number of Fuzzy Rules **RMSE** = Root Mean Square Error **MAPE** = Mean Absolute Percentage Error				

Each set of the 5 runs correspond to the use of the trimf, tramf, gbelmf, gaussmf and gauss2mf membership function types respectively. The table contains information of the number of fuzzy rules used for each case and the use of linear and non-linear parameters. For each case, the RMSE and the Mean Absolute Percentage Error, (MAPE) was calculated. The results show that, the best approach for the hybrid combination of 3-3-3 is the use of the trapezoid membership function with RMSE=4.78881 and MAPE=2.10136.
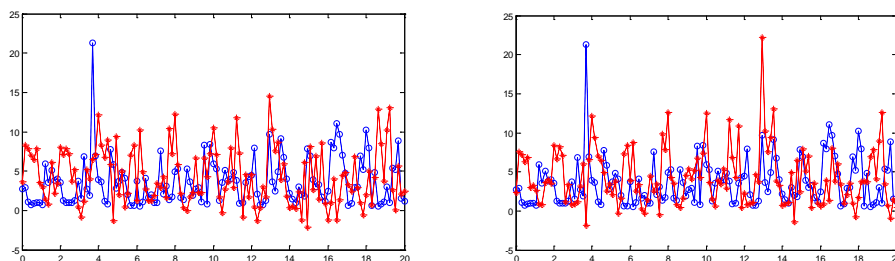

Fig. 6 Left) Observed and predicted time series with the 3-3-3 trapmf membership function configuration. Right) Observed and predicted time series with the 2-2-2 gbelmf membership function configuration.

On the other hand, the best approach for the hybrid combination of 2-2-2 is the use of the gbel membership function with RMSE=4.12944 and MAPE=1.92513.Based on RMSE results both indicated cases perform roughly equally in the range of average 5% error from the observed values. Figure 6 shows the predicted values of the groundwater recharge (red curve) against the observed (blue curve) for the two cases.

Conclusion and Future Challenges

In this work, we presented a novel approach in predicting the groundwater recharge of a watershed using temperature, precipitation and evapotranspiration time series data. The methodology uses an ANFIS where 70% of the available data participates in the learning process with the rest for testing the predicted values against the observed. The results are very promising reaching an almost 5% deviation from the observed values. We plan to model a similar technique for forecasting but with the use of Adaptive Neural Networks and Bayesian Neural Networks. We strongly believe that a combination of the three methodologies can provide a new and useful tool for hydrologists and modelers in managing water resources in a watershed.

Acknowledgement

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