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Modeling soil water content in extreme arid area using an adaptive neuro-fuzzy inference system

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Highlights

ANFIS model applied to modeling soil water content in extreme arid areas

The best fit of ANFIS model are compared with two artificial neural networks (ANN)

ANFIS model performed better than ANN in soil water content modeling

ANFIS model can be used as a tool for the modeling of soil water content.

SUMMARY

Modeling of soil water content (SWC) is one of the most studied 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 SWC in the extreme arid area. In- situ SWC datasets for soil layers, with depths of 40cm (layer1), 60cm (layer 2) below surface was taken for the present study. The models analyzed different combinations of antecedent SWC values and the appropriate input vector has been selected based on the analysis of residuals. The performance of the ANFIS models in training and validation sets are compared with the observed data. In layer 1, the model which consists of six antecedent values of SWC, has been selected as the best fit model for SWC modeling. On the other hand, which includes two antecedent values of SWC, has been selected as the best fit model for SWC modeling at layer 2. In order to assess the ability of ANFIS model relative to that of the ANN model, the best fit of ANFIS model of layer 1 and layer 2 structures are also tested by two artificial neural networks (ANN), namely, Levenberg–Marquardt

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feedforward neural network(ANN-1) and Bayesian regularization feedforward neural network(ANN-2). The comparison was made according to the various statistical measures. A detailed comparison of the overall performance indicated that the ANFIS model performed better than both the ANN-1 and ANN-2 in SWC modeling for the validation data sets in this study.

Keyword: Adaptive neuro fuzzy inference system; Neural networks; Soil water content; Modeling, Ejina basin

1. Introduction

Soil water content (SWC) 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. In arid area, SWC is one of the major control factors on the diversity, structure and function in ecosystem (Robinson et al., 2008). It provides the plant-available transpirable pool of water for its survival, the type of vegetation depends to a large extent on the amount and spatial distribution of soil moisture that is available to plants (Breshears and Barnes, 1999).

Various deterministic and stochastic models are available, which are utilized to simulate SWC. The deterministic models for soil water are commonly based on Richard's equation (Khan et al., 2003; Ragab et al., 2005; Shani et al.; 2007). The accuracy of soil moisture estimated by these models depends on the model physics, the number and configuration of soil layers, as well as on the temporal and spatial resolution of the input data (Elshorbagy and Parasuraman, 2008). Such models may require sophisticated mathematical tools, a significant amount of calibration data, and some degree of expertise and experience with the model. On the other hand, stochastic models are based on the direct relationship between the input and output data without having the complete physical understanding of the system. Much work has been done in deterministic models for simulating SWC. Recently, stochastic models such as artificial neural networks (ANNs) have attracted great interest due to their simple, fast and comparable performance in most cases compared with deterministic models (Zou et al., 2010).

Artificial neural networks (ANNs) approaches have been successfully applied in a number of diverse fields, rainfall–runoff simulation (Nourani et al., 2009; Ouarda and Shu, 2009; Talei et al., 2010; Wu and Chau, 2011), groundwater modeling (Banerjee et al., 2011; Chang et al., 2010; Kuo et al., 2004; Yoon et al., 2011), river flow forecasting (Adamowski and Sun, 2010; Chen and Chang, 2009; Chokmani et al., 2008; Misra et al., 2009; Nayak et al., 2004; Noori et al., 2011; Nour et al., 2006; Shu and Ouarda, 2007), and water quality modeling (Chan et al., 2007; Chaves and Kojiri, 2007a,b; Singh et al., 2009; Yan et al., 2010). A comprehensive review of the application of ANNs to hydrology can be found in the literature (ASCE Task Committee, 2000a, b; Maier and Dandy, 2000; Maier et al., 2010). However, the application of ANN to SWC modeling is limited in the literature (Elshorbagy and Parasuraman, 2008). To the knowledge of the author, few studies have been carried out to utilize the ANFIS technique in SWC modeling.

In arid land, since most of the fine roots (≤2 mm diameter) of desert species are the soil depth of 40-60 cm (Jackson et al.1996, 1997), we might expect that plant water uptake is limited by the SWC during this layers under conditions of high evaporative demand. The variation of SWC among this layer is very complicated owning the liquid and vapor transport or hydraulic redistribution of soil water by roots (Yu et al., 2013). In addition, the SWC is exceedingly low in arid regions. Therefore, simulations and predictions SWC within the plant root zone based on limited measured data is the challenge in this complicated environment. It is not clear whether ANFIS still have a good performance; this provided an impetus for the present investigation.

The main purpose of this study is to analyze the performances of an adaptive neuro-fuzzy (ANFIS) technique in SWC modeling using the antecedent SWC values data from two experimental soil layer, at depths of 40cm (layer1) and 60cm (layer 2) below surface in the extreme arid area of Ejina basin. The modeling accuracy of ANFIS model is compared with two different ANN techniques, namely, ANN-1 and ANN-2.

2. Materials and methods

2.1 Study area and data

Ejina basin, in the lower reaches of Heihe River as shown in Fig. 1, is one of the most arid areas in the world. The area covers 3×10^4 km^2, extending between latitudes $40^o20'$-$42^o30'$ N and longitudes $99^o30'$ –$102^o00'$ E. Owing to being in the hinterland of Asian continent, the region has an obvious characteristic of a continental climate that is extremely hot in summer and severely cold in winter, where the mean annual precipitation is 42 mm. The major part of the rainfall (about 60–70%) occurs during July to September. The mean annual potential evaporation is as high as 3,755 mm. Due to high variability and sparse precipitation, no perennial runoff originates from the area.

For the purpose of investigating SWC in Ejina basin, columns at two representative depths i.e., 40 and 60 cm were installed (41°58'53.95''N, 101°09'17.69''E，) located near Ejina City (Fig. 1). The soil texture profiles were silt loam soil with a clay interlayer. The SWC was continuously monitored using the EnviroSCAN, ICT Australian firm for the period May, 2004 to October, 2004. The measurement range of the equipment is between 0 to 100% Vol. and the accuracy is 1% after calibrating. The length of the probe is 20cm and the diameter is 32mm. The measurement depth varies from 40cm to 60 cm; moreover, each measurement depth is the same as the probe's length. The SWC for the two depths was recorded at 3-hour interval, providing 960 datasets. In this study, 900 data sets were selected as the available data. The data were divided into two sets: a training data set consisting of 630(70%) data sets and validation data set of 270(30%) data sets. The former was utilized to train and the later was applied to test models.

2.2 ANFIS

Adaptive neuro-fuzzy inference system (ANFIS), first introduced by Jang (1993), is a universal approximator and as such is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang et al., 1997). ANFIS is functionally equivalent to fuzzy inference systems (Jang et al., 1997). Specifically the ANFIS system of interest here is functionally equivalent to the Sugeno first-order fuzzy model (Jang et al., 1997; Drake, 2000). Below, the hybrid learning algorithm, which combines gradient descent and the least-squares method, is introduced.

As a simple example we assume a fuzzy inference system with two inputs *x* and *y* and one output *z*. The first-order Sugeno fuzzy model, a typical rule set with two fuzzy If-Then rules can be expressed as

$$\text{Rule 1 : If } x \text{ is } A_1 \text{ and } y \text{ is } B_1\text{; then } f_1 = p_1 x + q_1 y + r_1 \quad (1)$$

$$\text{Rule 2 : If } x \text{ is } A_2 \text{ and } y \text{ is } B_2\text{; then } f_2 = p_2 x + q_2 y + r_2 \quad (2)$$

where p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters in the then-part (consequent part) of the first-order

Sugeno fuzzy model. The architecture of ANFIS consists of five layers (Fig. 2), and a brief introduction of the model is as follows.

Layer 1: Each node of this layer generates membership grades to which they belong to each of the appropriate fuzzy sets using membership functions.

$$O_{1,i} = \mu_{Ai}(x) \qquad \text{for i=1,2} \tag{3}$$

$$O_{1,i} = \mu_{Bi-2}(y) \qquad \text{for i=3,4} \tag{4}$$

where x, y are the crisp input to the node i; A_i and B_{i-2} are the fuzzy sets associated with this node, characterized by the shape of the membership functions (MFs) in this node. A_i and B_{i-2} are the fuzzy set associated with this node, characterized by the shape of the MFs in this node and can be any appropriate functions that are continuous and piecewise differentiable such as Gaussian, generalized bell shaped, trapezoidal shaped and triangular shaped functions. The bell-shaped MF is used in this study

$$\mu_{Ai}(x) = \frac{1}{1+[(x-c_i)/a_i]^{2b_i}} \tag{5}$$

where $\{a_i, b_i, c_i\}$ is the parameter set that changes the shapes of the MF with maximum equal to 1 and minimum equal to 0.

Layer 2: This layer consists of the nodes labeled ∏which multiply incoming signals and sending the product out. For instance,

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi-2}(y) \; i\text{=1,2} \tag{6}$$

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio between the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i\text{=1,2} \tag{7}$$

Layer 4: Node i in this layer computes the contribution of the ith rule towards the model output, with the following node function:

$$O_{4,i} = \overline{w_i} f_i(p_i x + q_i y + r_i) \tag{8}$$

where $\overline{w}_i$ is the output of layer 3 and $\{p_i, q_i, r_i\}$ are the parameters set

Layer 5: The single node in this layer computes the overall output of the ANFIS as:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

The distinguishing characteristic of the approach is that ANFIS applies a hybrid-learning algorithm, the gradient descent method and the least-squares method, to update parameters. The gradient descent method is employed to tune premise non-linear parameters {ai,bi,ci}, while the least-squares method is used to identify consequent linear parameters {pi,qi, ri}. As shown in Fig. 2, the circular nodes are fixed (i.e., not adaptive) nodes without parameter variables, and the square nodes have parameter variables (the parameters are changed during training). The task of the learning procedure has two steps: In the first step, the least square method identifies the consequent parameters, while the antecedent parameters (MFs) are assumed to be fixed for the current cycle through the training set. Then, the error signals propagate backward. Gradient descent method is used to update the premise parameters, through minimizing the overall quadratic cost function, while the consequent parameters remain fixed. The detailed algorithm and mathematical background of the hybrid-learning algorithm have been in detail introduced by Jiang (1993).

In each application, different numbers of MFs were tried and the one that gives the minimum squared error was selected. Two bell-shaped MFs for the ANFIS models were found enough for modeling SWC.

2.3 ANFIS model development

In the development of ANFIS, the selection of appropriate input variables is important since it provides the basic information about the system being modeled. The current study analyzed different combinations of antecedent SWC values and the appropriate input vector was selected, based on the analysis of residuals. The ANFIS model was constructed and the analysis was started with one antecedent SWC in the input vector. The input vector is then modified by successively adding SWC at one more time lag, and a new ANFIS model is developed each time. The number of MFs assigned to each input of the ANFIS was initially set to two. The goodness of fit statistics was computed during training and validation for each ANFIS model and the best model is selected based on the analysis of residuals. Six ANFIS models and input structure in model structure of soil water content modeling (Table 1).

In order to assess the ability of ANFIS models relative to that of a neural network model, two ANN models were constructed using the same input parameters as the ANFIS model. Two types of three layer ANN models, each with one input layer, one hidden layer, and an output layer, were developed in this study. The first model (called ANN-1 model) employed the Levenberg–Marquardt algorithm whereas the second model (called ANN-2) employed the Bayesian regularization algorithm to train the investigated ANN architectures.

2.4 Artificial neural network (ANN)

Artificial neural network (ANN) is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1999). A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights and the activation function. The most commonly used neural network structure is the feedforward hierarchical architecture. A typical three-layered feedforward neural network is comprised of a multiple elements also called nodes, and connection pathways that links them (Hagan, 1995; Haykin, 1999). The nodes are processing elements of the network and are normally known as neurons, reflecting the fact the neural network method model is based on the biological neural network of the human brain. A neuron receives an input signal, processes it, and transmits an output signal to other interconnected neurons.

In the hidden and output layers, the net input to unit i is of the form

$$Z = \sum_{j=1}^{k} w_{ji} y_j + \theta_i \tag{10}$$

Where, w_{ji} is the weight vector of unit i and k is the number of neurons in the layer above the layer that includes unit i. y_j is the output from unit j, and y_i is the bias of unit i. This weighted sum Z; which is called the incoming signal of unit i, is then passed through a transfer function f to yield the estimates $\hat{y}_i$ for unit i. The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. The sigmoid transfer function, f_i, of unit i, is of the form

$$\hat{y}_i = \frac{1}{1+e^{-Z}} \tag{11}$$

A training algorithm is needed to solve a neural network problem. Since there are so many types of algorithms available for training a network, selection of an algorithm that provides the best fit to the data is required. Levenberg–Marquardt and Bayesian Regularization learning algorithms are used increasingly due to the better performance and learning speed with a simple structure.

2.4.1 Levenberg–Marquardt algorithm

The Levenberg–Marquardt algorithm (LMA), is similar to the quasi-Newton method in which a simplified form of the Hessian matrix (second derivative) is used. The Hessian matrix can be approximated as:

$$H = J^T J \tag{12}$$

and the gradient can be computed as

$$g = J^T e \tag{13}$$

Where, J is the Jacobian matrix which, contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. One iteration of this algorithm can be written as

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{14}$$

Where, μ is the learning rate and I is the identity matrix (Dedecker et al., 2004). During training, the learning rate μ is incremented or decremented by a scale at weight updates. When μ is zero, this is just Newton's method, using the approximate Hessain matrix. When μ is large, this becomes gradient descent with a small step size.

2.4.2 Bayesian regularization algorithm

Bayesian regularization is an algorithm that automatically sets optimum values for the parameters of the objective function. In the approach used, the weights and biases of the network are assumed to be random variables with specified distributions. In order to estimate regularization parameters, which are related to the unknown variances, statistical techniques are being used. The advantage of this algorithm is that whatever the size of the network, the function won't be over-fitted. Bayesian regularization has been effectively used in literature (Porter et al., 2000; Coulibaly et al., 2001a, b; Anctil et al., 2004; Krishna et al., 2008). A more detailed discussion of the Bayesian regularization can be found in the literature (MacKay, 1992).

2.5 Network performance evaluation

The performances of the models developed in this study were assessed using various standard statistical performance evaluation criteria. The statistical measures considered were root mean square error (RMSE), mean absolute error (MAE), and correlation of coefficient (R).

The root mean square error (RMSE) can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(SW_{observed,i} - SW_{modeled,i})^2} \tag{15}$$

The mean absolute error (MAE) can be calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|SW_{observed,i} - SW_{modeled,i}\right| \tag{16}$$

Coefficient of correlation (R) is defined as the degree of correlation between the measured and predicted values:

$$R = \frac{\sum_{i=1}^{n}(SW_{observed,i} - \overline{SW_{observed}})(SW_{modeled,i} - \overline{SW_{modeled}})}{\sqrt{\sum_{i=1}^{n}(SW_{observed,i} - \overline{SW_{observed}})^2 \sum_{i=1}^{n}(SW_{modeled,i} - \overline{SW_{modeled}})^2}} \tag{17}$$

Where, n is the number of input samples; $SW_{observed,i}$ and $SW_{modeled,i}$ are the measured and network output value from the i*th* elements, respectively. $\overline{SW_{observed}}$ and $\overline{SW_{modeled}}$ are their average, respectively.

It appears that while assessing the performance of any model for its applicability in modeling SWC, it is not only important to evaluate the average prediction error but also the distribution of prediction errors. The statistical performance evaluation criteria employed so far in this study are global statistics and do not provide any information on the distribution of errors. Therefore, in order to test the robustness of the model developed, it is important to test the model using some other performance evaluation criteria such as average absolute relative error (AARE) and threshold statistics for an absolute relative error (ARE) level of x% (TS_x) (Jain and Indurthy, 2003; Nayak et al., 2004). The AARE not only gives the performance index in terms of predicting flows but also the distribution of the prediction errors.

The AARE and TS_x can be calculated as follow:

$$AARE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{SW_{observed,i} - SW_{\mathrm{mod}eled,i}}{SW_{observed,i}}\right| \tag{18}$$

$$TS_X = \frac{n_x}{n} \times 100\% \tag{19}$$

where, n_x is the number of data points for which the ARE is less than x%, n the total number of data points computed. Clearly, lower AARE values and higher TSx values would indicate good model performance.

3. Results and discussion

3.1 Layer 1

The ANFIS models are compared based on their performance in training sets and validation sets. The results are summarized in Table 2. From Table 2, it is apparent that all of the models performed similarly as the values of RMSE and MAE don't vary significantly, and all R are also very close to unity. It also shows that the Model 6, which consists of six antecedent SWC in input, has the smallest value of the RMSE (4.72440E-04) and MAE (3.35676E-04) and higher value of R (0.99994) than other models in the training period. It also has the lower value of the RMSE (1.55592E-04) and higher value of R (0.99303) than other models in the validation period. Thus, it is selected as the best-fit model for describing the time series of SWC in the layer 1.

In order to assess the ability of ANFIS model relative to the neural network model, two ANN models are developed using the input combinations of Model 6 ($x[t\text{-}1]$ $x[t\text{-}2]$ $x[t\text{-}3]$ $x[t\text{-}4]$ $x[t\text{-}5]$ $x[t\text{-}6]$). The ANN-1 model was trained using the Levenberg–Marquardt training algorithm, and the optimal number of neuron in the hidden layer was identified using a trial and error procedure by varying the number of hidden neurons from 2 to 20. Further, the optimal network architecture was selected based on the one with minimum of RMSE. The final ANN architecture consists of twelve nodes. Therefore an ANN-1 with six input neurons, twelve hidden neurons and one output neuron (6-12-1) was adopted as the best structure. In order to have a true comparison, the structure and the number of hidden neurons in ANN-2 model were maintained similar to that of ANN-1 model (6-12-1) except that in ANN-2 model, the training algorithm was a Bayesian regularization.

The performances of the ANFIS and the ANN models in terms of the RMSE, MAE and R at training and validation stages of layer 1 are presented in Table 3. It was found that the difference between the values of the statistical indices of the training and validation set does not vary substantially. However, the ANFIS model performed a bit better than both ANN-1 and ANN-2 model. Concretely, ANFIS model produced a lower RMSE and MAE as well as higher R, the former being the best. The second best performance was ANN-2 model, trained with the Bayesian regularization algorithm, The ANN-1 was found to be the worst of all approaches investigated in this study.

Fig. 3 and Fig.4 show the scatter plots of both the observed data and the modeled obtained by using the ANFIS, ANN-1 and ANN-2 model of the validation period. The Fig. 3, and Fig. 4 reveal that both the model showed good prediction accuracy of the SWC. As seen from the fit line equations, the ANFIS model show more accuracy than ANN models, the performance of the ANN-2 is better than the model ANN-1.

Analyzing the results from Table 4, the AARE for the ANFIS model is significantly lower (0.068%) compared to the ANN-1 (0.132%) and ANN-2 (0.087%) during validation, highlighting its superiority over the ANN-1 and ANN-2 models.

The statistics of ARE levels during validation in layer 1were obtained by the ANFIS, ANN-1 and ANN-2 model. A maximum of 42.96% had AREs less than 0.05% (TS0.05 during validation) and 98.52% had AREs less than 0.2% (TS0.2) from the ANFIS model (Table 4); and the corresponding values for ANN-1 and ANN-2 model were 17.41%, 34.08% and 77.78%, 94.07%, respectively. Therefore, ANFIS model was the most effective model in terms of modeling SWC accurately during validation set as shown in TS and AARE statistics. The second best performance was obtained by using the ANN-2 model, and the ANN-1 was found to be the worst of all approaches investigated in layer 1.

3.2 Layer 2

The RMSE, MAE and R statistics of the different ANFIS model test results for the layer 2 are given in Table 5. It was found that all of the models performed similarly as the values of RMSE and MAE don’t vary significantly, and all R are also very close to unity in the training period. It also shows that the Model 2, which consists of two antecedent SWC in input, has the smallest value of the RMSE (7.30003E-04), MAE (6.87646E-04) and higher value of R (0.96422) than other model in the validation set, so, it is selected as the best-fit model for describing the time series of SWC in the layer 2.

The performances of the ANFIS and the ANN models in terms of the RMSE, MAE and R at training and validation stages of layer 2 are presented in Table 6. Like layer 1, the difference between the values of the statistical indices of the training and validation set does not vary substantially, and the ANFIS model performed a bit better than both ANN-1 and ANN-2 model. However, unlike layer 1, the second best performance was ANN-1 model, trained with the Levenberg–Marquardt algorithm, and the ANN-2, was found to be the worst of all approaches investigated in the layer 2.

Fig. 5 and Fig.6 show the scatter plots of both the observed and the modeled SWC obtained by using the ANFIS, ANN-1 and ANN-2 model of the validation period. The Fig. 5, 6 reveal that both the models showed good prediction accuracy for high values of SWC but were unable to maintain their accuracy for lower values of flow. The reason for the low accuracy of the models at low SWC event may be that the series of SWC of training set is highly skewed and shows heteroscedasticity, and the low SWC values are not contained in the training set (Fig. 7).

The AARE for the ANFIS model is significantly lower (0.245%) compared to the ANN-1 (0.368%) and ANN-2 (0.481%) during validation, highlighting its superiority over the ANN-1 and ANN-2 models in layer 2.

The statistics of ARE levels during validation in layer 2 were obtained by the ANFIS, ANN-1 and ANN-2 model. A maximum of 94.81% had AREs less than 0.4% (TS0.4 during validation) and 100% had AREs less than 0.6% (TS0.6) from the ANFIS model (Table 7); and the corresponding values during testing from ANN-1,ANN-2 model were 62.22%, 17.77% and 97.78%, 91.11%, respectively. Therefore, ANFIS model was the most effective model in terms of modeling SWC accurately in layer 2 during validation, the second best performance was obtained for ANN-1 model, and the ANN-2 was found to be the worst of all approaches investigated in layer 2.

Comparing the performances of the ANFIS and ANN models, RMSE and MAE values of ANFIS models are lower than those of two ANN models. In addition, values of R of ANFIS model are also higher than those of two ANN models. Thus, it can be concluded that, the performance of

ANFIS method is better than ANN method according to the criteria. The results demonstrate that ANFIS method is superior to the ANN method in the modeling of SWC.

4. Conclusion

This study investigated the applicability of ANFIS method for SWC modeling in the extreme arid areas of Ejina basin. SWC was studied at two depths, i.e., 40cm and 60cm below surface. The results of ANFIS models and observed values were compared and evaluated based on their training and validation performance. The results demonstrated that ANFIS can be applied successfully to estimate accurate and reliable SWC. According to results, in layer 1, Model 6, which consists of six antecedent values of SWC, has been selected as the best fit model for SWC modeling. On the other hand, Model 2, which includes two antecedent values of SWC, has been selected as the best fit model for SWC modeling at layer 2.

In order to assess the ability of ANFIS model relative to the neural network model, two ANN models were investigated, namely, ANN-1 and ANN-2 model, which were developed using the input combinations as the selected ANFIS model. The comparison was made according to the various statistic measures. ANFIS model was found to perform much better than the ANN models in SWC modeling for both the considered soil layers. The results suggested that ANFIS model provides accurate estimation of SWC and can be successfully applied for SWC forecasting. ANFIS model can be particularly relevant for forecasting SWC without getting deeper into underlying physical relationships or when there are limited input data for driving numerical models. Further, the results presented here were promising and ANFIS model can be successfully applied to forecasting SWC with complicated pedologic environment within the plant root zone.

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Reference

Adamowski, J., Sun, K., 2010. Development of a coupled wavelet transform and neural network method for flow forecasting of non-perennial rivers in semi-arid watersheds. Journal of Hydrology 390, 85-91.

Anctil.F., Filion. M., Tournebize, J., 2009. A neural network experiment on the simulation of daily nitrate-nitrogen and suspended sediment fluxes from a small agricultural catchment. Ecological Modelling 220,879-887.

Aqil, M., Kita, I., Yano, A., Nishiyama, S., 2007. A comparative study of artificial neural networks and neuro-fuzzy in continuous modeling of the daily and hourly behaviour of runoff. Journal of Hydrology 337, 22-34.

ASCE Task Committee, 2000a. Artificial neural networks in hydrology—I: preliminary concepts. J. Hydrol. Eng. 5, 115–123.

ASCE Task Committee, 2000b. Artificial neural networks in hydrology—II: hydrologic applications. J. Hydrol. Eng. 5, 124–137.

Banerjee, P., Singh, V.S., Chatttopadhyay, K., Chandra, P.C., Singh, B., 2011. Artificial neural network model as a potential alternative for groundwater salinity forecasting. Journal of Hydrology 398, 212-220.

Breshears, D.D. and Barnes, F.J., 1999. Interrelationships between plant functional types and soil moisture heterogeneity for semiarid landscapes within the grassland/forest continuum: a unified conceptual model. Landsc. Ecol., 14(5): 465-478.

Chan, W.S., Recknagel, F., Cao, H., Park, H.D., 2007. Elucidation and short-term forecasting of microcystin concentrations in Lake Suwa (Japan) by means of artificial neural networks and evolutionary algorithms. Water research 41, 2247-2255.

Chang, F.-J., Kao, L.-s., Kuo, Y.-M., Liu, C.-W., 2010. Artificial neural networks for estimating regional arsenic concentrations in a blackfoot disease area in Taiwan. Journal of Hydrology 388, 65-76.

Chaves, P., Kojiri, T., 2007a. Conceptual fuzzy neural network model for water quality simulation. Hydrological Processes 21, 634-646.

Chaves, P., Kojiri, T., 2007b. Deriving reservoir operational strategies considering water quantity and quality objectives by stochastic fuzzy neural networks. Advances in Water

Resources 30, 1329-1341.

Chen, Y.-h., Chang, F.-J., 2009. Evolutionary artificial neural networks for hydrological systems forecasting. Journal of Hydrology 367, 125-137.

Chokmani, K., Ouarda, T.B.M.J., Hamilton, S., Ghedira, M.H., Gingras, H., 2008. Comparison of ice-affected streamflow estimates computed using artificial neural networks and multiple regression techniques. Journal of Hydrology 349, 383-396.

Coulibaly, P., Anctil, F., Aravena, R., Bobe´e, B., 2001a. Artificial neural network modeling of water table depth fluctuations.Water Resource Research. 37, 885–896.

Coulibaly, P., Bobee, B., Anctil, F., 2001b. Improving extreme hydrologic events forecasting using a new criterion for artificial neural network selection. Hydrological Processes 15, 1533–1536.

Dedecker, A.P., Goethals, P.L.M., Gabriels,W., De Pauw, N., 2004. Optimization of artificial neural network (ANN) model design for prediction of macro invertebrates in the Awalm river basin (Flanders Belgium). Ecol. Model. 174, 161–173.

Drake, J.T., 2000. Communications phase synchronization using the adaptive network fuzzy inference system. Ph.D. Thesis, New Mexico State University, Las Cruces, New Mexico, USA.

Elshorbagy, A., Parasuraman, K., 2008. On the relevance of using artificial neural networks for estimating soil moisture content. Journal of Hydrology 362, 1-18.

Hagan MT, Demuth H, Beale M. Neural networkdesign. 20 ParkPlaza, Boston, MA: PWS Publishing Company;1995.

Haykin S. Neural network-a comprehensive foundation. Englewood Cliffs, NJ: Prentice-Hall; 1999.

Jackson RB, Canadell J, Ehleringer JR, Mooney HA, Sala A, Schulze E-D, 1996. A global analysis of root distributions for terrestrial biomes. Oecologia 108:389–411.

Jackson RB, Mooney HA, Schulze E-D. 1997. A global budget for fine root biomass, surface area, and nutrient contents. Proc Natl Acad Sci 94:7362–7366.

Jain, A., Indurthy, S.K.V.P., 2003. Comparative analysis of event based rainfall-runoff modeling techniques-deterministic, statistical, and artificial neural networks. Journal of

Hydrologic Engineering ASCE 8 (2), 93–98.

Jang JSR. 1993ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst, Man, Cybernet;23(3):665–85.

Jang, J.S.R., Gulley, N., 1995. The Fuzzy Logic Toolbox for Use with MATLAB. The Mathworks, Inc., Natick, MA.

Jang, J.S.R., Sun, C.T., Mizutani, E., 1997. Neuro-fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. Prentice-Hall, New Jersey

Khan, S., Xevi, E., Meyer, W.S., 2003. Salt, water, and groundwater management models to determine sustainable cropping patterns in shallow saline groundwater regions of Australia. Journal of Crop Production 7, 325–340.

Krishna, B., Satyaji Rao, Y.R., Vijaya, T., 2008. Modelling groundwater levels in an urban coastal aquifer using artificial neural networks. Hydrological Processes 22, 1180-1188.

Kuo, Y.M., Liu, C.W., Lin, K.H., 2004. Evaluation of the ability of an artificial neural network model to assess the variation of groundwater quality in an area of blackfoot disease in Taiwan. Water research 38, 148-158.

MacKay D.J.C., 1992. Bayesian interpolation. Neural Computation 4,415–447.

Maier, H.R., Dandy, G.C., 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environmental Modelling & Software 15:101–124.

Maier, H.R., Jain, A., Dandy, G.C., Sudheer, K.P., 2010. Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions. Environmental Modelling & Software 25, 891-909.

Misra, D., Oommen, T., Agarwal, A., Mishra, S.K., Thompson, A.M., 2009. Application and analysis of support vector machine based simulation for runoff and sediment yield. Biosystems Engineering 103, 527-535.

Nayak, P., Sudheer, K., Rangan, D., Ramasastri, K., 2004. A neuro-fuzzy computing technique for modeling hydrological time series. Journal of Hydrology 291, 52-66.

Noori, R., Karbassi, A.R., Moghaddamnia, A., Han, D., Zokaei-Ashtiani, M.H., Farokhnia, A., Gousheh, M.G., 2011. Assessment of input variables determination on the SVM model performance using PCA, Gamma test, and forward selection techniques for monthly stream flow prediction. Journal of Hydrology 401, 177-189.

Nour, M., Smith, D., Eldin, M., Prepas, E., 2006. The application of artificial neural networks to flow and phosphorus dynamics in small streams on the Boreal Plain, with emphasis on the role of wetlands. Ecological Modelling 191, 19-32.

Nourani, V., Komasi, M., Mano, A., 2009. A Multivariate ANN-Wavelet Approach for Rainfall–Runoff Modeling. Water Resources Management 23, 2877-2894.

Ouarda, T.B.M.J., Shu, C., 2009. Regional low-flow frequency analysis using single and ensemble artificial neural networks. Water Resources Research 45.

Porter, D.W., Gibbs, P.G., Jones, W.F., Huyakorn, P.S., Hamm, L.L., Flach, G.P., 2000. Data fusion modeling for groundwater systems. Journal of Contaminant Hydrology 42, 303–335.

Ragab, R., Malash, N., Abdel Gawad, G., Arslan, A., Ghaibeh, A., 2005. A holistic generic integrated approach for irrigation, crop and field management: 1. The SALTMED model and its calibration using field data from Egypt and Syria. Agricultural Water Management 78, 67–88.

Robinson, D.A., Campbell, C.S., Hopmans, J.W., Hornbuckle, B.K., Jones, S.B., Knight, R., Ogden, F., Selker, J. and Wendroth, O., 2008. Soil moisture measurement for ecological and hydrological watershed-scale observatories: A review. Vadose Zone J, 7(1): 358-389.

Shani, U., Ben-Gal, A., Tripler, E., Dudley, L.M., 2007. Plant response to the soil environment: an analytical model integrating yield, water, soil type, and salinity. Water Resource Research 43 (Article number W08418).

Shu, C., Ouarda, T.B.M.J., 2007. Flood frequency analysis at ungauged sites using artificial neural networks in canonical correlation analysis physiographic space. Water Resources Research 43.

Singh, K.P., Basant, A., Malik, A., Jain, G., 2009. Artificial neural network modeling of the river water quality—A case study. Ecological Modelling 220, 888-895.

Singh, K.P., Malik, A., Basant, N., Saxena, P., 2007. Multi-way partial least squares modeling of water quality data. Anal. Chim. Acta 584, 385–396.

Talei, A., Chua, L.H.C., Wong, T.S.W., 2010. Evaluation of rainfall and discharge inputs used by Adaptive Network-based Fuzzy Inference Systems (ANFIS) in rainfall–runoff modeling. Journal of Hydrology 391, 248-262.

Wu, C.L., Chau, K.W., 2011. Rainfall–runoff modeling using artificial neural network coupled with singular spectrum analysis. Journal of Hydrology 399, 394-409.

Yan, H., Zou, Z., Wang, H., 2010. Adaptive neuro fuzzy inference system for classification of water quality status. Journal of Environmental Sciences 22, 1891-1896.

Yoon, H., Jun, S.-C., Hyun, Y., Bae, G.-O., Lee, K.-K., 2011. A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. Journal of Hydrology 396, 128-138.

Yu, T. F., Feng, Q., Si, J. H., Xi, H. Y., Li, W., 2013. Patterns, magnitude, and controlling factors of hydraulic redistribution of soil water by *Tamarix ramosissima* roots. Journal of Arid Land, 5(3): 396-407.

Zou, P., Yang, J., Fu, J., Liu, G., Li, D., 2010. Artificial neural network and time series models for predicting soil salt and water content. Agricultural Water Management 97, 2009-2019.

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Table 7. TS and AARE values of various models for layer 2

Table 1 Model structure of soil water content modeling

ANFIS model	Input structure
Model 1	$x(t)=f(x[t-1])$
Model 2	$x(t)=f(x[t-1]\ x[t-2])$
Model 3	$x(t)=f(x[t-1]\ x[t-2]\ x[t-3])$
Model 4	$x(t)=f(x[t-1]\ x[t-2]\ x[t-3]\ x[t-4])$
Model 5	$x(t)=f(x[t-1]\ x[t-2]\ x[t-3]\ x[t-4]\ x[t-5])$
Model 6	$x(t)=f(x[t-1]\ x[t-2]\ x[t-3]\ x[t-4]\ x[t-5]\ x[t-6])$

where $x(t)$ corresponds to the soil water content at time t.

Table 2. The *RMSE*, *MAE*, *R* statistics of each model in training and validation periods for layer 1.

Model	Training			Validation		
	RMSE	MAE	R	RMSE	MAE	R
Model 1	7.10017E-04	5.23268E-04	0.99987	1.59697E-04	1.24363E-04	0.99258
Model 2	6.46695E-04	4.65151E-04	0.99990	1.73071E-04	1.38964E-04	0.99187
Model 3	6.19431E-04	4.39292E-04	0.99990	1.55891E-04	1.22903E-04	0.99292
Model 4	5.49523E-04	3.89852E-04	0.99992	1.56393E-04	1.23247E-04	0.99294
Model 5	4.97502E-04	3.47539E-04	0.99994	1.55751E-04	1.23088E-04	0.99298
Model 6	4.72440E-04	3.35676E-04	0.99994	1.55592E-04	1.23517E-04	0.99303

Table 3. Performance evaluation statistics of various models for Layer 1

Model	Training			Validation		
	RMSE	MAE	R	RMSE	MAE	R
ANFIS	4.72440E-04	3.35676E-04	0.99994	1.55592E-04	1.23517E-04	0.99303
ANN-1	5.24431E-04	3.81576E-04	0.99993	2.80875E-04	2.40068E-04	0.99012
ANN-2	5.10757E-04	3.61107E-04	0.99993	1.94260E-04	1.57868E-04	0.99189

Table 4. TS and AARE values of various models for layer 1

Model	TS0.02	TS0.05	TS0.1	TS0.2	AARE
ANFIS	20.74	42.96	75.09	98.52	0.068
ANN-1	9.63	17.41	39.26	77.78	0.133
ANN-2	14.44	34.08	62.22	94.07	0.087

Table 5. The *RMSE*, *MAE*, *R* statistics of each model in training and validation periods for layer 2.

Model	Training			Validation		
	RMSE	MAE	R	RMSE	MAE	R
Model 1	3.38432E-03	1.14000E-03	0.96988	7.37677E-04	6.92189E-04	0.95935
Model 2	3.06935E-03	1.09409E-03	0.97529	7.30003E-04	6.87646E-04	0.96422
Model 3	2.96621E-03	1.01525E-03	0.97694	1.25540E-03	1.20939E-03	0.94122
Model 4	2.92679E-03	1.00745E-03	0.97756	2.03115E-03	1.98093E-03	0.93133
Model 5	2.86284E-03	9.43480E-04	0.97854	1.99533E-03	1.94822E-03	0.94553
Model 6	2.74206E-03	8.71469E-04	0.98033	3.18405E-03	3.10152E-03	0.89629

Table. 6 Performance evaluation statistics of various models for layer 2

Model	Training			Validation		
	RMSE	MAE	R	RMSE	MAE	R
ANFIS	3.06935E-03	1.09409E-03	0.97529	7.30003E-04	6.87646E-04	0.96422
ANN-1	3.12913E-03	1.08432E-03	0.97431	1.07182E-03	1.03294E-03	0.96580
ANN-2	3.12722E-03	1.09142E-03	0.97434	1.37918E-03	1.34787E-03	0.96389

Table 7. TS and AARE values of various models for layer 2

Model	TS0.3	TS0.4	TS0.5	TS0.6	AARE
ANFIS	82.96	94.81	98.12	100.00	0.245
ANN-1	17.41	62.22	92.22	97.78	0.369
ANN-2	4.07	17.77	57.78	91.11	0.481

Figure list

Fig. 1. Location of study area and the soil water content measuring site

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Fig.6 Comparison of the observed and modeled soil water content values in validation set of layer 2

Fig.7 Results of the observed soil water content in the training data set of layer 2

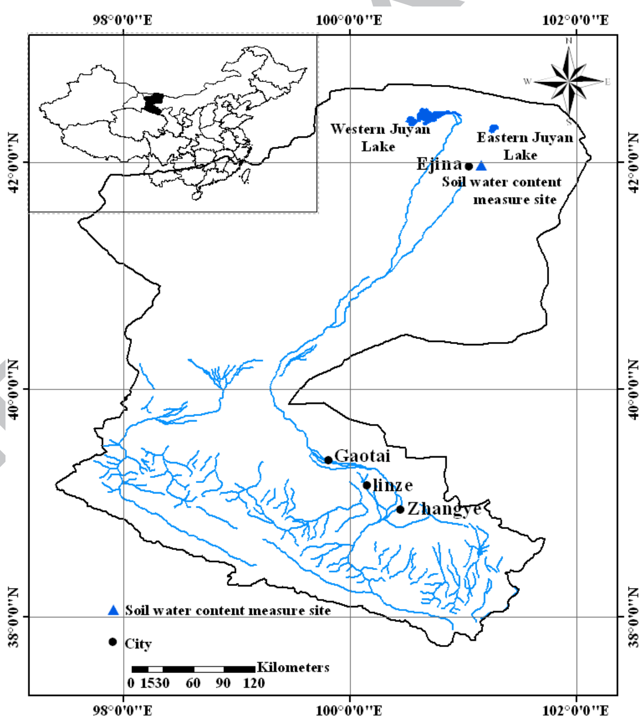

Fig. 1 Location of study area and the soil water content measuring site

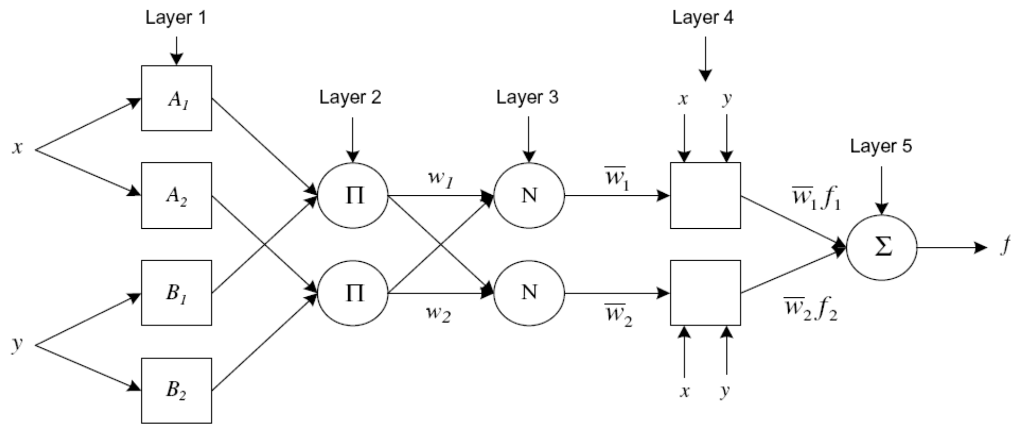

Fig. 2. Architecture of the ANFIS

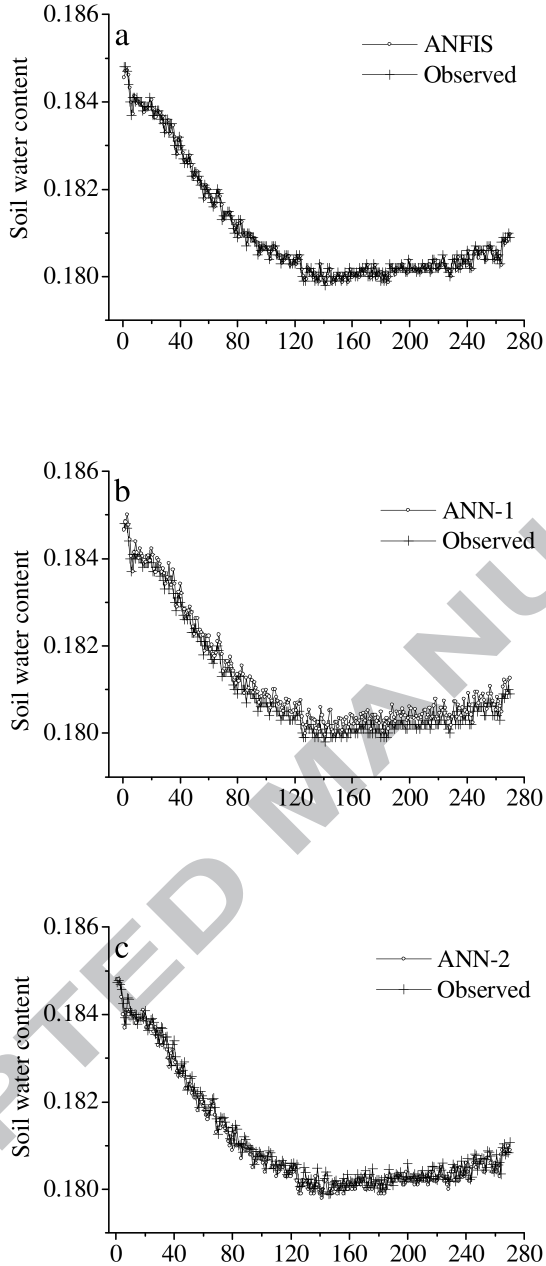

Fig.3 Results of the observed and modeled soil water content values in validation set of layer 1.

a,b,c is ANFIS, ANN-1 and ANN-2 model, respectively

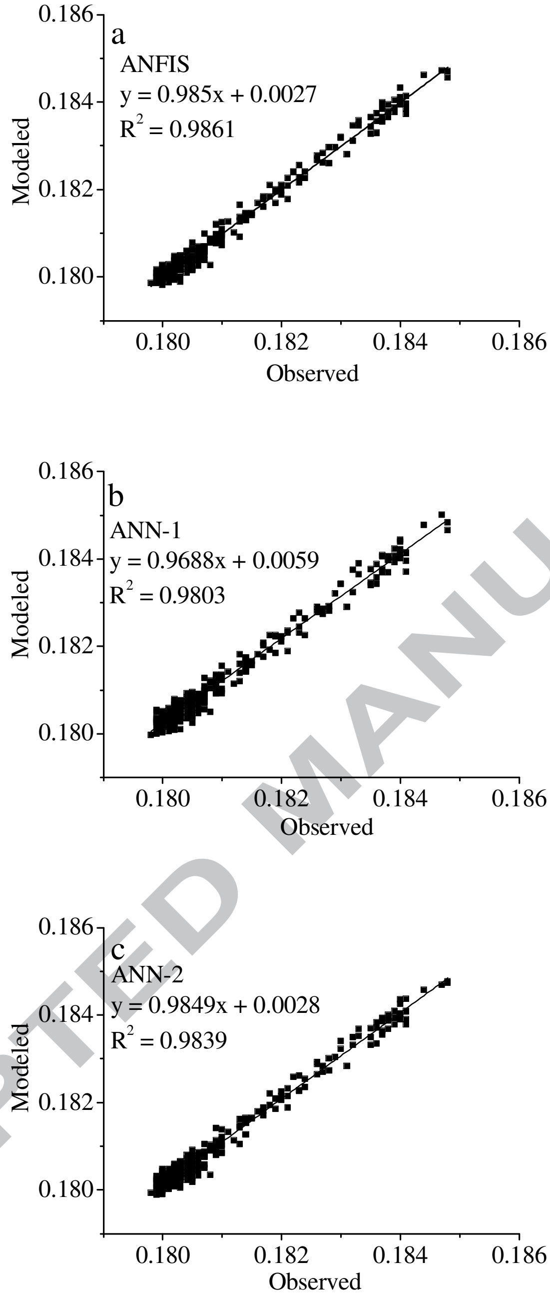

Fig.4 Comparison of the observed and modeled soil water content values in validation set of layer 1

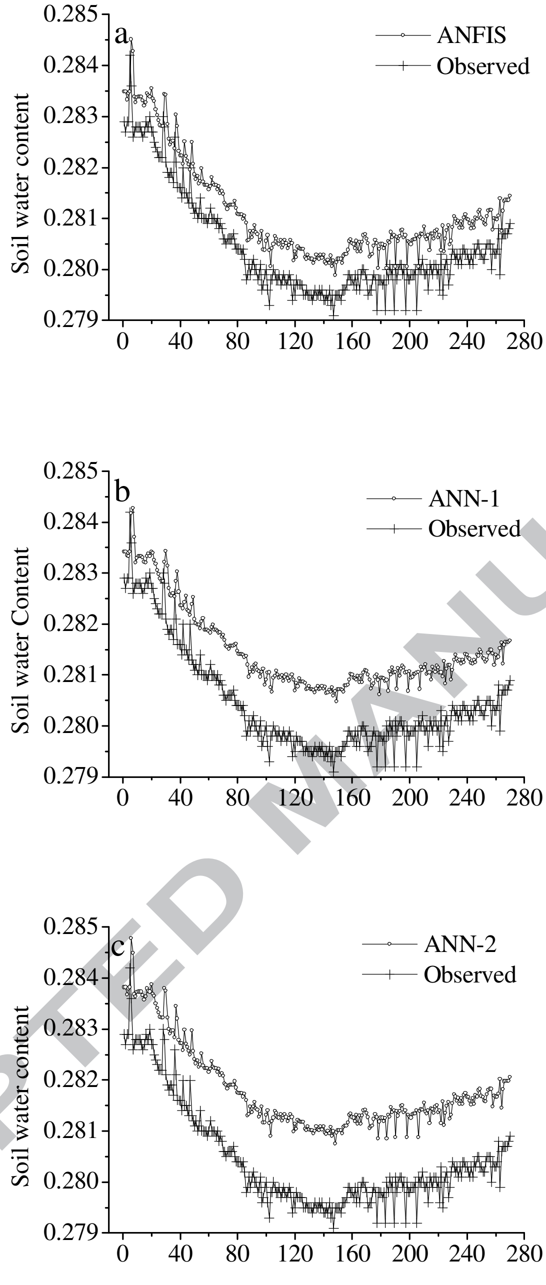

Fig. 5 Results of the observed and modeled soil water content values in validation set of layer 2.

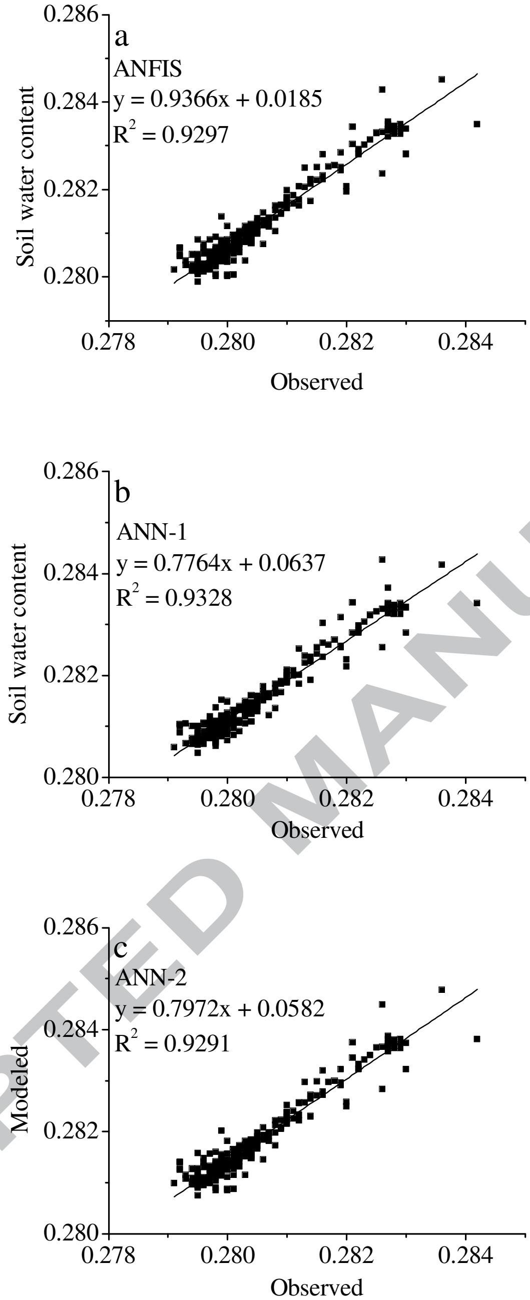

Fig.6 Comparison of the observed and modeled soil water content values in validation set of layer 2

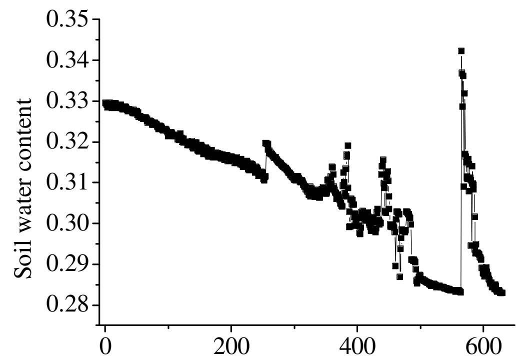

Fig.7 Results of the observed soil water content in the training data set of layer 2

Highlights

ANFIS model applied to modeling soil water content in extreme arid areas

The best fit of ANFIS model are compared with two artificial neural networks (ANN)

ANFIS model performed better than ANN in soil water content modeling

ANFIS model can be used as a tool for the modeling of soil water content.