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DOI:
10.3103/S1068373921060066

Enhanced Long-term and Snow-based Streamflow Forecasting by ANN and Neuro-fuzzy Techniques Using Satellite Imagery and Seasonal Information

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Abstract

This paper investigates the simultaneous use of in-situ hydrologic measurements, such as discharge, temperature, precipitation and snowfall information derived from satellite imagery in combination with two different AI methods, namely, Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN), for developing enhanced long-term streamflow forecasting models. To enhance the reliability of the proposed models' outputs, the number of input data used for their training and testing is increased using a sub-basin method. Furthermore, to accelerate the training process and achieve more accurate handling of seasonal changes, a parameter representing seasonal variations is introduced. A regionalization approach is also proposed to overcome the problem of deficiency and inappropriate distribution of hydro-meteorological stations in poor data regions. To obtain the most principal input variable set to be used in developing the models, a gradual model development approach is proposed and followed. In summary 12 streamflow forecasting models based on ANFIS, ANN and using three different model structures and two forecast time intervals (monthly, seasonal) are developed. The models are applied to data collected from the mountainous Talezang basin located in the southwestern Iran, which consists of 14 years of monthly measurements including streamflow, precipitation, temperature, and snow water equivalent (SWE) records and snow cover area obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS). The results indicate that the use of the sub-basin approach significantly improves both models' performances, as indicated by the improvement of the correlation coefficient index (R) from 0.44, to 0.77 in the testing phase. Moreover, it is deduced that including additional input parameters in the model structure, as well as using seasonal information and satellite data, has a great impact on the model's performance and accuracy, evident by the reduction of the scatter index (SI) by 35% on average. Comparing the long-term flow forecasts of both models showed that ANFIS is superior to ANN. It is concluded that the ANFIS method, developed based on data from the proposed sub-basin method and seasonal parameter, is capable of providing high quality streamflow forecasts, particularly for rivers and streams located in data poor regions.

Keywords: AI methods, regionalization approach, Satellite images, Seasonality index, Streamflow forecasting.

1. Introduction

Streamflow forecasting has an important role in water resources management activities including flood control, drought management and reservoir operation. Accurate streamflow estimation can theoretically be made by using the many hydrologic and climatologic variables (e.g., precipitation, evapotranspiration, initial moisture, temperature, discharge etc.) that are known to affect short and long-term streamflow predictions. The lead-time provided by these models creates an opportunity to adjust and change operating policies and management procedures in order to cope with near future contingent events, such as droughts and floods.

Streamflow forecasting models are categorized according to their lead-time (extending from one hour to one year in length), forecasting time step (hourly to seasonal), dominant precipitation regime (rain and/or snow) and basin characteristics (e.g., land use and cover, topography, and slope). Due to the differences in these attributes, many different approaches have been followed to develop and improve streamflow forecasting models.

The review of the literature indicates that a wide range of physical and conceptual models (e.g. Demirel et al., 2009; Noori and Kalin, 2016) have been used for developing streamflow forecasting models. Despite their advantages, e.g. ease of use and high-level understanding of the system, conceptually based streamflow models may not be suitable for application in large and complex basins. Therefore, alternative approaches are proposed to improve forecasting in such settings.

Many black box modeling approaches have been also used to develop streamflow forecasting models. These include regression-based methods (e.g. Phien et al., 1990; Liu et al., 2018), time series models (e.g. Jain et al., 2001), artificial neural networks (ANNs) (e.g. Sajikumar and Thandaveswara, 1999; Uysal and Şorman, 2017); Adaptive Neuro Fuzzy Inference System (ANFIS) (e.g. Chang and Chang, 2006; Rezaeianzadeh et al., 2014) and a combination of some of these methods (e.g. Pulido and Portela, 2007; Dariane and Azimi, 2016; Nourani et al., 2014; Yaseen et al., 2015). In general, appropriate performance in large and complex systems and having reliable and unbiased outcomes can be listed as the main advantages of black box methods. Many studies reported in the literature, including the ones listed above, indicate the superiority of black box-based flow forecasting models particularly in predicting peak flows.

In the past two decades, methods based on ANNs have been adopted and proven to be more flexible, successful and dependable alternatives to regression methods for modeling nonlinear systems which include different parameter types such as watershed characteristics, hydrometric and climatic parameters at various lead times (daily, monthly) (e.g. see Prada-Sarmiento and Obregon-Neira, 2009; Choubin et al., 2016). Despite their numerous advantages, including the capability of parallel computation, capacity of fault tolerance, adaptive training ability and requiring no prior knowledge, the disadvantages of ANNs, such as disability in processing ambiguous data and difficulty in building a general purpose model for the inclusion of future changes in the system, have led to ANNs being combined with other techniques, such as Fuzzy inference systems (FISs), in order to improve their performance (e.g., Taormina and Chau, 2015).

Despite the merits of ANNs and FISs (linguistic description, human thinking and mathematical reasoning), both ANNs and FISs do have specific shortcomings. ANNs cannot be properly developed with insufficient and poor data, and on the other hand, if the knowledge (i.e. regarding observed data and parameters) is incomplete or contradictory, a fuzzy system should be tuned following a heuristic approach, which can be time consuming and error prone. Hence, combining these two methods, in order to benefit from the advantages of both methods in a complementary way, and overcome their disadvantages, will be advantageous.

Among different hybrid models, Adaptive Neuro-Fuzzy Inference System (ANFIS) takes the advantage of the two methods in a complementary way. Due to its advantages, ANFIS has attracted more attention and has been widely used in hydrologic modeling including reservoir inflow and streamflow forecasting (Karimi-Googhari and Lee, 2011; Azad et al., 2018). Talei et al., (2010) used neuro-fuzzy and Storm Water Management Model (SWMM) to forecast streamflow in the Kranji basin in Singapore. Analyzing statistical indices, such as relative Peak Error (EP), they concluded that ANFIS performs better than SWMM at peak flows. For example, average EP values for all events improves from 0.31 in SWMM to 0.26 in ANFIS.

Although the discussed models are relatively successful in predicting streamflow in certain basins, due to some limitations, they are not generalizable to basins of other sizes and located in other geographical regions. These limitations are generally related to 1) not counting for bimodal climate, 2) not considering snowfall, and 3) being based on point data observations.

In many regions of the world (e.g., tropical Atlantic and Pacific equatorial regions), climate is bimodal, meaning that there are two distinct seasonal patterns: in the winter months frontal rainfall associated with low evaporation occurs, and in summer months, climate is associated with convective rainfall and high evapotranspiration (ET). Since this trend repeats over a long period of time, black box methods which consider variations in seasonal climate are believed to enhance model accuracy and performance, in comparison with those that lump all seasons together (Garbrecht, 2006). In this study, a calendar month identification scheme is proposed to be used as an effective approach for capturing the effects of seasonal variations.

Another important issue in hydrologic studies is the deficiency and inappropriate distribution of hydro-meteorological stations. This often leads to poor model accuracy, making them unsuitable, especially for long-term forecasting. Furthermore, in most previous studies, observed point data from stations have been used instead of areal estimates in forecasting models (e.g., Shiri and Kisi, 2010). Use of point data may be applicable in small basins, but it would introduce errors if the basin is large. This problem is intensified when several parameters (e.g., precipitation and temperature) are included in the model. To overcome this problem, in this study, the basin is divided into some sub-basins and the outflow data for each sub-basin is used as the response value of the system for those sub-basin areal data (i.e., precipitation, etc.).

Finally, another important factor in accurate streamflow forecasting in mountainous basins is snowfall. Therefore, remote sensing knowledge derived from satellite imagery that help in estimating the amount of snow (coverage, depth and snow water equivalent) can be of great use in developing appropriate forecasting models. In recent decades, technological progresses in the field of sensors and satellites along with easy and free accessibility to satellite images has been an important factor for advancements in snow-based streamflow forecasting models. There are some promising cases where satellite images have been successfully used in various hydrological studies and streamflow forecasting (e.g. Singh and Jain, 2003; Nagler et al., 2008; Cornwell et al., 2016). Here, it is proposed to use snow water equivalent (SWE) records and snow cover area from the Moderate Resolution Imaging Spectroradiometer (MODIS) in combination with in-situ measurements to develop enhanced models.

This study aims to address the aforementioned shortcomings in streamflow forecasting, by developing accurate and robust models for use in poorly-gauged mountainous basins. The proposed models are based on two black box approaches (ANFIS, ANN) and are developed using a combination of remote sensing data with in-situ observations. The models are used to forecast monthly and seasonal streamflow in the mountainous Talezang basin, located in the southwestern Iran. In order to evaluate the effect of seasonal variations on the models, a parameter called seasonality parameter, is introduced and applied for long-term streamflow forecasting. In addition, it is shown that the use of areal data, using a regionalization approach, could enhance the results obtained by the models. **2. Background**

2.1. Artificial Neural Networks

Artificial neural networks (ANNs) are based on the structure and functioning of the human brain and are composed of processing elements in each layer called neurons (Hagan et al., 1996). The model is trained by adjusting the weights in an attempt to minimize the sum of squared errors between the model output and model target (observed data).

The feed-forward neural network concept is the most common approach for forecast modeling. The hydrologic events are often classified as complex and nonlinear models, because of the non-linear characteristics of its variables. Therefore a Multilayer perceptron (MLP) feed-forward neural network including one input layer, one output layer with a linear transfer function and two hidden layers with hyperbolic tangent sigmoid transfer function is commonly applied. The number of hidden layers is identified based on a trial-and-error method with the objective being the best model performance. The back-propagation (BP) algorithm, which is the main method for training networks used for prediction, is applied to adjust the weight vectors between layers with an objective to minimize the mean square error (MSE) between predicted and target values. This process consists of two steps: first, the input signal (discharge, rainfall, temperature, etc.) is propagated forward to compute the output (discharge). Then, a backward step is used to adjust the weight vectors between layers with the objective to minimize the model's error (Hagan et al., 1996). Moreover, for speeding up convergence, the Levenberg-Marquart algorithm (Moré, 1978), which is more powerful and faster than conventional techniques, such as gradient descent, is combined with the back-propagation algorithm.

2.2. Adaptive Neuro Fuzzy Inference System (ANFIS)

Novel architecture and learning procedure for Fuzzy inference systems (FISs) was first introduced by Jang (1993). This system is a multi-layer feed-forward network which uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate Membership Functions (MFs) from the stipulated input-output pairs. This developed procedure of FIS using adaptive neural networks is called Adaptive Neuro Fuzzy Inference System (ANFIS). ANFIS has been used successfully for many hydrological studies (e.g. Rezaeianzadeh et al., 2014, Akil et al., 2007, Ozgür, 2006).

Generally, the ANFIS model architecture consists of five layers (Figure 1). Selection of the FIS type based on the specific target system is important. In the current study the Sugeno first-order fuzzy model (Sugeno and Kang, 1988) is used since the consequent part of the FIS model (p_i, q_i, r_i) is a linear equation and the parameters can be calculated by a simple Least Square Error (LSE) method.

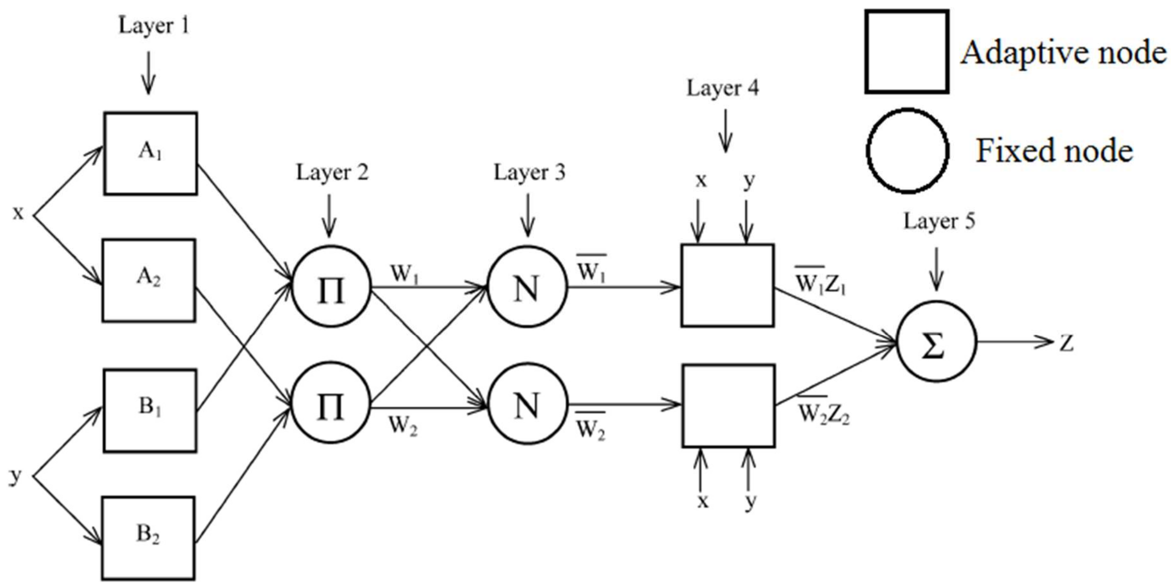


Figure 1. Basic structure of the ANFIS (Jang, 1993)

For instance, consider that the FIS has two inputs (x, y) and one output as shown in Figure (1). For the first order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: if x is A_1 and y is B_1 then $z_1= p_1x+q_1y+r_1$ (1)

Rule 2: if x is A_2 and y is B_2 then $z_2= p_2x+q_2y+r_2$ (2)

where A and B are the semantic words and membership function of x and y, respectively. The output z is the weighted average of the individual rule outputs and p_i, q_i, r_i are the consequent parameters, which are determined during the learning process. It should be noted that nodes at the same layer have similar functions. The 5 layers of ANFIS are be described as below:

Layer 1: Every node i in this layer is an adaptive node with a node function. The output of the i^{th} node at layer 1 is defined as O_i^1:

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

Or

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

where x (or y) is the crisp value of one of the input variables to the i^{th} node and A_i (or B_{i-2}) is the linguistic label associated with this node function. O_i^1 is the membership function of A_i (or B_{i-2}) which is used to generate a membership grade. The membership function for A and B are usually described by a bell-shaped function with a maximum equal to 1 and minimum equal to 0 such as:

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

where (a_i, b_i, c_i) are referred to as the premise parameters.

Layer 2: every node in this layer is a fixed node labeled "Π" that multiplies the incoming signals. Each output node represents the incentive intensity of a rule. For instance,

$$O_i^2 = \omega_i = \mu_{Ai}(x).\mu_{Bi}(y), i = 1,2 \tag{6}$$

where $\overline{\omega}_i$ is the output of layer i.

Layer 3: each node in this layer is a fixed node shown as N. The i[th] node in this layer, calculates the ratio of the i[th] rule's incentive intensity to the sum of all rules' incentive intensity and its output is called normalized incentive intensity. The ratio is found by:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1,2 \tag{7}$$

Layer 4: node i[th] in this layer is an adaptive node. The output of every node can be computed through defuzzification process as follows:

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + r_i), i = 1,2 \tag{8}$$

where $\overline{\omega}_i$ is the output of layer 3, and (p_i, q_i, r_i) is the parameter set referred to as consequent parameters.

Layer 5: the single node in this layer is a fixed node labeled "Σ" that calculates the final output as the summation of all input signals which can be calculated by:

$$O_i^5 = \sum_{i=1}^{2} \overline{\omega}_i f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} \tag{9}$$

Finally, the overall output can be expressed as a linear combination of the consequent parameters:

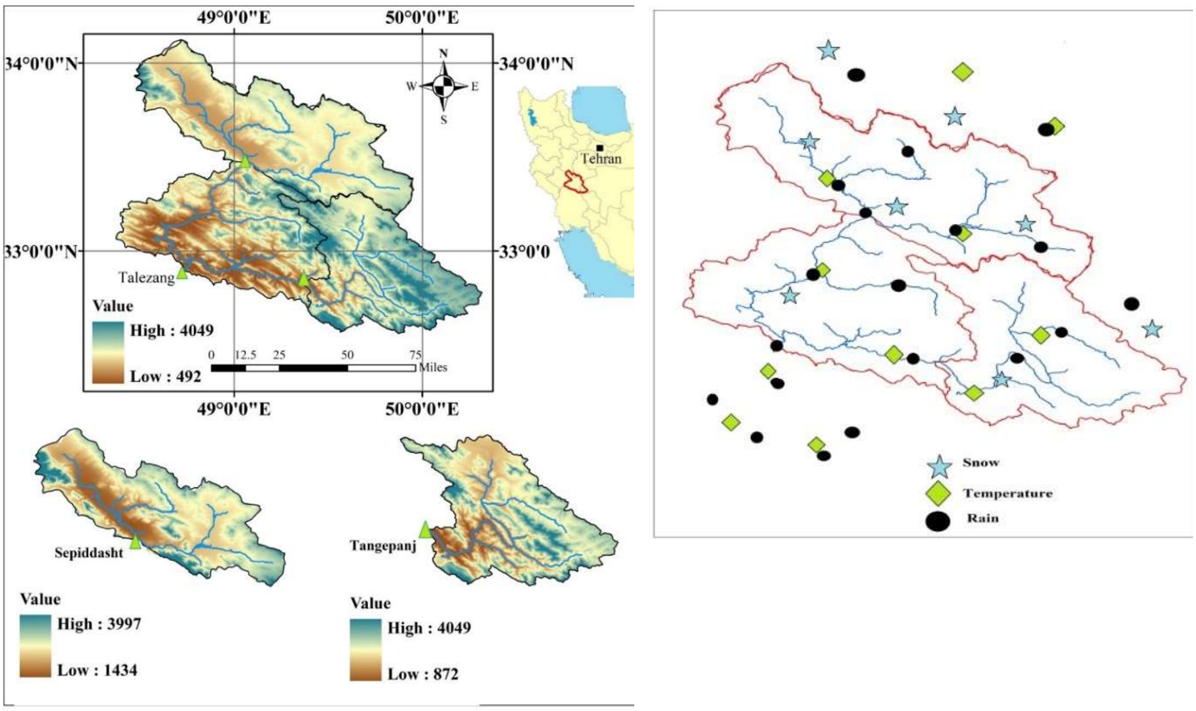
$$z = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 = (\overline{\omega}_1 x) p_1 + (\overline{\omega}_1 y) q_1 + (\overline{\omega}_1) r_1 + (\overline{\omega}_2 x) p_2 + (\overline{\omega}_2 y) q_2 + (\overline{\omega}_2) r_2 \tag{10}$$

It is notable that the learning rule determines how the premise parameters (fixed parameters a_i, b_i and c_i in Layer 1) and consequent parameters (p_i, q_i and r_i in Layer 4) should be updated in order to minimize the error using a least squares estimator. A hybrid learning algorithm, which combines backpropagation gradient descent and least-square methods, and consists of 2 steps, namely, forward and backward transmission, is commonly used. The least-squares method (forward transmission) leads to finding optimum consequence parameters (pi, qi, ri). The gradient descent method (backward transmission) is applied immediately in order to optimally adjust the premise parameters (ai, bi, ci) (Raghupathi, 1996).

Finally, the obtained consequent parameters are used to calculate the output of the ANFIS model. More details on ANFIS model are available in Jang (1997).

3. Case study and data

The Talezang basin, located in the central region of Zagros Mountains, SW Iran, was selected as the case study basin. This basin has a total area of just under 17000 km^2 and maximum and minimum heights of 4049 and 492 meters above sea level, respectively, meaning that the basin is in a mountainous region. The basin has east-west slope and its spatial domain extends from 32° 50' to 34° 00' Northern latitude and from 48° 30' to 50° 30' Eastern longitude. Two discharge stations (m^3/sec), namely, the Sepiddasht and Tangepanj stations are located at the outlets of sub-basins on the Sezar and Bakhtiari rivers, respectively, and the Talezang station is located at the outlet of the basin downstream of the junction of these two rivers (Figure 2a).



(a) (b)

Figure 2. (a) Talezang case study basin overview, and the location of Talezang, Sepiddasht and Tangepanj streamflow stations, (b) location of rain, snow and temperature stations in the study site.

The data used in this study consisted of:

- Digital Elevation Model (DEM) operated on Shuttle Radar Topography Mission (SRTM) with spatial resolution of 90 m. This information was used in the model to extract regional relations between parameters (discussed further in the methods section)

- Monthly in-situ observations of hydrometrical and metrological variables. These consisted of monthly average streamflow measured at the outlet of each sub-basin (Figure 2a), monthly rainfall, monthly average temperature and monthly snow measurement stations (Figure 2b).

- Processed images of TERRA-MODIS sensor (MOD10A2) corresponding to each forecasting month (months of December, January, February, March, April, May during 2002-2015).

4. Methodology

4.1. Snow-Cover Mapping using MODIS

Snow has an undeniable effect on any hydrological event, but due to some issues, such as inappropriate distribution of in-situ observations, the use of snow data normally leads to error-prone representation of hydrologic processes. It is, however, shown that outputs from optical sensors can be used to overcome this shortcoming in hydrological modeling (e.g. Immerzeel et al., 2009; Powel et al., 2011).

To extract snow information for the study basin, the outputs from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments were used, because of their accuracy, availability and high time and space resolution (Rittger et al., 2013). This instrument is operational on two Earth Observation System (EOS) spacecrafts: Terra (launched December 1999, overpassing the equator at 10:30 a.m.) and Aqua (launched May 2002, overpassing the equator at 1:30 p.m.). More information on MODIS can be found in Hall et al., (2002).

In this study, the data from the MODIS instruments on the Terra spacecraft were utilized to obtain snow maps and perform long-term stream forecasts. Among all MODIS products, maximum snow cover extent (MOD10A2) was adopted, because of its merits, which include better snow-mapping accuracy and better cover. MOD10A2 provides maximum snow cover extent during an eight-day period. It is generated by reading 8 days of 500 m resolution

MOD10A1 tiles, which provides daily gridded snow cover. If snow is observed in a cell on any day in the period, the cell is mapped as snow. If no snow is found, the cell is assigned with the clear-view observation that has been mostly reported for that cell (e.g. snow free land, lake, etc.). Cloud cover is only reported if the cell was cloud-obscured during the entire eight day period. Each cell's snow/no snow chronology is recorded using bit flags and provided as a separate variable. The maximum snow extent is where snow was observed on at least one day during the period (Hall and Riggs, 2015). All MODIS products are freely available to download from https://nsidc.org.

In MODIS, the Normalized Difference Snow Index (NDSI) is introduced as a helpful criterion for identifying snow, ice and many precluding factors of snow cover acquisition (e.g., cumulus clouds). The NDSI snow-mapping index uses reflectance values in MODIS band numbers 4 (0.545-0.565 μm) and 6 (1.628-1.652 μm) (Hall et al., 1998):

$$NDSI = \frac{Band4 - Band6}{Band4 + Band6} \tag{11}$$

where *Band*4 and *Band*6 are the MODIS band 4 and band 6 reflectance values, respectively. A pixel in a non-densely forested region will be mapped as snow if NDSI ≥ 0.4.

Additionally, for a pixel to be covered with snow, the reflectance of MODIS *Band* 2 (0.841-0.876 μm) should be more than 11%. Also, MODIS *Band* 4 reflectance is a useful criterion to separate real snow cover from spurious snow cover (e.g., spruce forests). Therefore, it is required that the MODIS *Band* 4 reflectance is greater than 10%. It is to be noted that all criteria should be met simultaneously for each pixel in order for that pixel to be mapped as a snow pixel (Hall et al., 1998).

This output consisted of two types of pixels, non-snow and snow pixels, which were marked with black and white pixels, respectively, on images. This procedure was repeated on all satellite images from the study basing during 14 years from 2002-2015, and the findings were converted into snow and non-snow pixels. Finally, after extracting snow pixels, Snow Cover Area (SCA) for the sub-basin was calculated by adding the area of all snow-covered pixels.

4.2. Sub-basin approach

Data based methods such as ANN and ANFIS require a sufficient amount of representative data to properly model the system and yield acceptable prediction accuracy. To overcome this problem, the number of input data can be increased through a sub-basin segmentation approach where the basin is simply divided into a number of sub-basins, determined based on appropriate distance and location from each other. It is notable that river's length, catchment's slope and ridges play important role in sub-basin formation (Fig. 2a).

Following this approach, the mountainous and data poor Talezang study basin was divided to 3 sub-basins as shown in Figure (2a). The outflow data for each sub-basin (Sepiddasht and Tengepanj), represents the response of the system to precipitation in that particular sub-basin. Therefore, using these new observations the data available for training and testing the models is tripled.

4.3. Regional relationships approach

For basins, such as the selected study basin, where there is a lack of measurements in high altitude ranges and the distribution of stations is inappropriate, using point data for the entire basin is deemed erroneous and will lead to unreliable model outputs. A regional relations approach, derived from point data is proposed to overcome this problem.

In this approach, first, regional relationships are established by regressing the pixel elevation of each station against separate in-situ records (e.g. temperature, precipitation and SWE) for each desired month. Once these regional relationships are derived for each parameter, their values in each pixel are computed and then averaged over the sub-basin to calculate an average parameter value in the corresponding month. SCA values at each sub-basin are calculated by applying the snow-mapping algorithm corresponding to each sensor. Therefore, the volume of SWE for each sub-basin can be obtained through multiplying corresponding SCA in average SWE values.

4.4. Seasonal Parameter

Historic data shows that measured streamflow in the basin has strong seasonality with significant annual cycle. Therefore, it was envisaged that a seasonal parameter would enhance the modeling if implemented in the development of the ANN and ANFIS forecasting models. To capture the effects of seasonal rainfall and runoff variations, calendar month identification was performed. To account for seasonal variability, two time series, representative of the cyclic 12 months of the year, were added to the previous input variable sets, i.e. temperature, precipitation and SWE. These two series are represented by a pair of oscillating sine and cosine curves. For each month, there is one unique data pair, thus, the entire annual cycle is represented by 12 cyclic pairs (Figure 3). It is apparent from the two time series that the seasonal conditions of January follow those of December.

4. 5. Model Development

To develop ANN and ANSIF models for the data poor Talezang basin, first, the number of observed data from the system was increased by dividing the basin into three sub-basins as described in section 4.2.

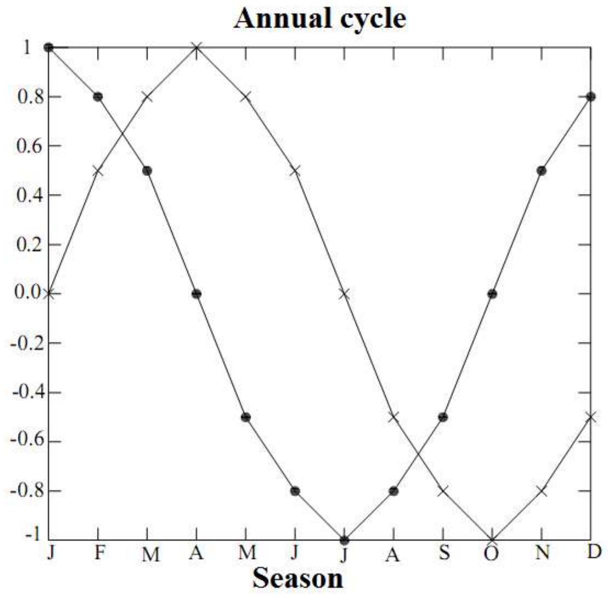


Figure 3. Two time series representing the annual cycle

Due to inappropriate distribution of stations and insufficient in-situ measurements particularly at higher altitudes, access to reliable data for the entire basin was challenging. Therefore, the regional relations approach, described in section 4.3, was followed to obtain reliable data.

The data period used for training and testing consisted of 14 years of data (2002-2015). The first 10 years of data (nearly 75% of the whole dataset) was utilized for training the models and the remaining 4 years were kept for the testing phase. Forecasting was carried out for 6 months starting from January throughout June in each year. This period was selected based on the availability of snow cover in the basin in order to be used as input data.

The set of input variables to be used in the models were obtained through a gradual development approach, by testing different variable combinations based on statistical indices including coefficient of correlation (R), Scatter Index (SI) and the partial auto-correlation function (PCF) of monthly streamflow data. In order to investigate the effect of each variable set on the model's performance, the model structure was gradually developed in three steps. In the first step, only hydrometric and meteorological data, such as discharge, rain, temperature were considered (model I, Eq.12.I). In the next step a combination of products from optical sensors and in-situ records, lumped in the volume of snow water equivalent (V_{swe}) was added to the variable set (model II, Eq.12.II). Finally, seasonal information as a month identification tool was added to the model structure (model III, Eq.12.III). As highlighted in section 4.4, these two inputs are representative of the cyclic 12 months of the year, but in the present study these parameters are limited to the forecast period which start from January through June. The three model structures are:

$$Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, P_{t-1}, T_{t-1}) \tag{12.I}$$

$$Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, P_{t-1}, T_{t-1}, Vswe_{t-1}) \tag{12.II}$$

$$Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, P_{t-1}, T_{t-1}, Vswe_{t-1}, t_1, t_2) \tag{12.III}$$

where Q_t is the predicted streamflow in month t (m^3/sec), Q_{t-1} to Q_{t-3} are streamflows in the previous three months (m^3/sec), P_{t-1} is precipitation in the previous month (Million Cubic Meters, MCM), T_{t-1} is the average temperature of the previous month (°C), V_{swet-1} is the volume of snow water equivalent corresponding to the previous month (MCM) and t_1, t_2 are the pairs of seasonal information, derived from the annual cycle (Figure 3).

Different forecast intervals can be appropriate for assessing models in different situations. For example, longer predictions (e.g., seasonal, annual) are suitable for models where their predictions are used to design reservoir operation policies. In the present study, the focus is on predicting streamflow in two long-term intervals: monthly and seasonal. Seasonal forecasting is the process of forecasting in next three consecutive months. Since the architecture of the models developed and used in the study (e.g., ANFIS, ANN) are only based on one output, therefore, compulsively, the average values of streamflow for the next three months are computed and utilized as the output for the seasonal forecasting model.

Selection of appropriate number of nodes in the hidden layer is of great importance; too many neurons may lead to over-fitting, and on the other hand, if too few neurons are considered, the network might be unable to describe the underlying functions adequately. Fletcher and Goss (1993) proposed a range for the suitable number of nodes in a hidden layer that extends from ($2n^{1/2}$ + m) to (2n + 1), where n is the number of input nodes and m is the number of output nodes. Therefore, the number of neurons in each hidden layer is optimized by applying a trial-and-error approach in a specified range considering the number of inputs in each model combination (models I, II and III). In summary, streamflow forecasting is performed by two methods (ANFIS, ANN), using three different model structures (models: I, II, III) and two forecast time intervals (monthly, seasonal). The statistical criteria deemed appropriate for evaluating the models' performance were chosen to be the coefficient of correlation (R), Root Mean Square Error (RMSE) and Scatter Index (SI), which is computed as the ratio of RMSE to mean observed streamflow $\overline{Q_0}$:

$$SI = \frac{RMSE}{\overline{Q_0}} \tag{13}$$

5. Results and discussions

5. 1. ANN models

First, ANN models were developed to forecast monthly and seasonal streamflow at the Talezang basin outlet. Table (1) shows the performance of the ANN models with different model structures (i.e. Models I, II, III). As it can be seen, the model's performance for the test data is improved by adding new variables. For instance, the coefficient of correlation R in model (III) shows improvements of 7% in monthly and 16% in seasonal forecasting as compared to model (I). A similar trend is observed for the SI index. This improvement is logical since more variables can potentially better cover the characteristics and properties of the data, and thus, the more comprehensive model will be able to describe the underlying functions better. But it's also important that more variables can lead to overfitting. Therefore, considering a trade-off between more accuracy and avoidance of overfitting is necessary for having a robust and reliable model.

Table 1. Comparison of the performances of ANN-based models for the test period (2012-2015).

	ANN Model	R	SI	RMSE
Monthly	**(I)**	0.79	0.68	81.06
	(II)	0.80	0.74	87.23
	(III)	0.82	0.58	68.82
Seasonal	**(I)**	0.65	1.05	116.08
	(II)	0.63	0.85	94.39
	(III)	0.75	0.77	85.08

It is hypothesized that the effect of parameters (precipitations, discharge, temperature and snow) on a model's performance generally decreases with the selection of a larger forecasting time step, and therefore, it is expected that the model's accuracy in seasonal predictions is lower than its monthly predictions. Comparison between the results of monthly and seasonal streamflow predictions confirms this hypothesis. For example, the maximum values of R in monthly and seasonal predictions by model III are 0.82 and 0.75, respectively. A similar trend is observed for other statistical indices.

5.2. ANFIS models

Next, the performance of ANFIS-based streamflow forecast models were assessed in an approach identical to the one used for ANN models. The results (Table 2) indicate improvements in the ANFIS model performance in predicting both monthly and seasonal streamflow, as a more complete set of variables are used. For instance, the SI index for monthly forecast improved by about 29% in model (III) in comparison with that of model (I). It is also observed that there is considerable improvement in ANFIS results in predicting monthly streamflow in comparison with seasonal streamflow. This trend is identical to the trend observed for ANN models, and as mentioned before, it appears to be the result of decreased effect of parameters on the model outputs with increase in forecasting length.

Table 2. Comparison of the performances of ANFIS-based models for the test period (2012-2015).

	ANFIS Model	R	SI	RMSE
Monthly	**(I)**	0.79	0.67	80.80
	(II)	0.86	0.50	59.46
	(III)	0.84	0.48	57.25
Seasonal	**(I)**	0.70	1.03	114.46
	(II)	0.69	0.79	57.65
	(III)	0.76	0.71	78.55

Looking at ANFIS and ANN streamflow prediction results, it can be concluded that adding input variables to the model structure improves the model performance and helps in better describing the observed trends. It should be noted that adding variables does not necessarily end up in evaluation index improvements for all considered statistical indices. In fact, sometimes a decline in these indices is found which is contradictory to the general trend. For instance, general improvements of the R index due to adding new variables is not seen in monthly forecasts of ANFIS model (III) in comparison with model (II).

As expected, the use of remote sensing knowledge was able to enhance model performance significantly, as evident by the results. For instance, for both models (ANN, ANFIS), model (II) outperforms model (I) in both monthly and seasonal predictions as indicated by all statistical indices. Therefore, it can be concluded that interfering snow in-situ records, especially when combined with remote sensing knowledge, is a necessary step in hydrologic modeling of streamflow in mountainous basins. Unfortunately, the use of satellite images is not common practice in hydrologic studies. The lack of using satellite images in forecast models maybe related to the difficulties in processing this kind of data and also time and computational burdens. But, considering the considerable improvement this can lead to in terms of model performance, inclusion of this kind of data seems necessary and makes the difficulties worthwhile.

Results shown in Tables (1) & (2) also demonstrate that for both soft computing models (ANN, ANFIS) inclusion of seasonal information improved the model performance in both monthly and seasonal predictions. The obtained SI value in monthly ANN model (II) is 0.74, whereas this value is improved by about 20% to 0.58, when seasonality information is applied (model III). Moreover, a similar trend is observed in the other statistical goodness of fit measures (RMSE and R), for different cases. Based on the results, it becomes evident that using only previous streamflow data in conjunction with precipitation, temperature and snow records as inputs is not sufficient for accurate streamflow forecasting. It is necessary to include Information about the season and time of the year alongside in-situ observations to obtain an accurate model structure.

Based on the three statistical criteria reported in Tables (1) & (2), it can be seen that the ANFIS model outperforms the ANN model in all settings. The superiority of the ANFIS model is more significant when the most sophisticated model structure (Model III), which considers all effective parameters in forecasting model, is considered. This ability stems from the structure of the ANFIS model, and also the simultaneous inclusion of the benefits of adaptive neural network and fuzzy logical systems.

5.3. Effect of regional data on model performance

Using point data in hydrologic studies has two major advantages over using non-point data. First, it avoids the extra work and calculations required for extracting regional parameters. Second, when point data is available, usually, there is sufficient number of observations from the stations that can be used in the model. However, inefficiency in large basin and poor distribution of data can be listed as disadvantages of the point data approach.

In most previous studies that have focused on using soft computing methods for developing black-box hydrologic models (e.g. Shiri and Kisi, 2010, Uysal and Şorman, 2017), station observations have been used instead of areal estimates. This is mainly due to the hope that the inherent flexibility in soft computing methods, as a result of appropriate adjustments of weight parameters during the calibration process, would take care of the insufficiency of poorly distributed in-situ measurements, especially in large basins.

In this section, it is shown that the high inherent flexibilities assumed in black-box methods, is not entirely valid, and that the utilization of regional parameters would substantially improve the model's performance. To this end, model combination (I), that entirely consists of in-situ recorded variables, was re-developed using point data and its performance was compared to the results of the model developed using areal data (presented in sections 5.1 and 5.2). To apply point data in the Talezang basin, the average value of monthly rain and temperature stations in the entire basin and three previous monthly streamflow data were used as inputs to the forecast model. The final outlet (Talezang station at the corresponding month) for the basin was identified as the basin's outlet discharge station and monthly forecasts covering 6 months (January- June) were used.

The results of this comparison are presented in Table (3). As can be seen, the incremental improvements in using regional data over point station data are considerable in both black-box models (ANN and ANSIF).

Table 3. Comparison of Model I's performance developed based on point and regional data.

Methods	Areal data			Station data		
	R	SI	RMSE	R	SI	RMSE
ANN – Model I	0.77	0.68	81.06	0.44	0.84	106.32
ANFIS - Model I	0.79	0.67	80.8	0.49	0.77	98.43

The results for the test period indicate that when areal data is used, models' performances are improved considerably. For instance, the correlation coefficient index R for ANFIS and ANN models using point station data is 0.49 and 0.44, whereas, these values are improved to 0.79

and 0.77, respectively, when areal data is used. A similar trend can be seen for other statistical goodness of fit measures. Therefore, it can be concluded that for the basin analyzed in this study, i.e. the Talezang basin, and possibly in many other cases, utilization of a multiple sub-basin approach along with areal data could potentially enhance the results of black-box streamflow forecast models.

6. Conclusions

This paper presented a methodology for developing accurate long-term streamflow forecasting models using two soft computing methods, namely ANN and ANFIS. Historic records of in-situ observation, including monthly streamflow, precipitation and temperature, a snow parameter, i.e. volume of snow water equivalent (SWE), and seasonal information were used as inputs for training and building streamflow forecasting models. A method was suggested for obtaining SWE values from MODIS satellite images. It was deemed that using seasonal information would increase model reliability, thus a parameter representing seasonality was introduced and considered in the model. Additionally, to enhance model training, a sub-basin approach was employed to increase the input data which had naturally reduced in number as result of regionalization. To assess the sensitivity of the models to the set of introduced input data and to select an appropriate model structure, model training was performed in three stages, where more variables were added at each stage. The methods were applied to the mountainous Talezang study basin in SW Iran and the following main results were obtained:

- In general, and for all 3 investigated model structures, ANFIS models outperformed ANN in predicting streamflow.
- Deriving a snow parameter such as SWE from satellite images, and using it alongside other in-situ observation records, improves the results of streamflow predictions in both ANN and ANSIF models.
- For both ANN and ANSIF models, monthly forecast models are superior to seasonal models.
- Rebuilding the model using point data and comparing the results, it was shown that utilizing regional data could substantially enhance the prediction of streamflow forecast models, particularly in mountainous poor data basins.

- It was also shown that using seasonal information as input parameter can enhance the results of ANN and ANFIS-based forecasting models.

7. References

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