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Development of a Hydrologic Model Using Artificial Intelligence for Upper Euphrates Basin in Turkey

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Abstract: Streamflow forecasting has a great significance in hydrology, water resources planning and management studies. Either long term or short term forecasts of streamflows are necessary to optimize the operation of water resources systems. Artificial neural networks (ANNs), which is a popular widely used Artificial Intelligence (AI) method, is relatively new nonlinear statistical approach which has the capability to model complex nonlinear hydrological processes without physical expression. It is an alternative modelling approach that is inspired by brain and nervous systems to conventional hydrological models. This paper describes implementation of an ANN to forecast catchment flows in a snow dominated mountainous basin named Karasu Basin, which is the headwater of Euphrates Basin in Turkey. Due to non-availability of proper snow data, catchment flows were predicted by using only meteorological data. A best meteorological data set was investigated to achieve best performance of the model. Results of ANN model simulations were compared with the well-established conceptual index models, Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) and Large Basin Runoff Model (LBRM).

Key words: Hydrological modelling • Artificial Neural Networks • Catchment flow • Streamflow estimation • Upper Euphrates Basin

INTRODUCTION

Streamflow forecasting has a great significance in hydrology, water resources planning and management studies. Either long term or short term forecasts of streamflows are necessary to optimize the operation of water resources systems. In addition, accurate flow forecasts strongly influence feasible river management [1]. Thus, streamflow simulation and forecasting has been one of the most important tasks in efficient water resources planning, design and management for hydrologists. There are many papers in literature on streamflow simulation and forecasting. Most of those papers focused on ungauged flow estimations based on historical streamflow data [2, 3] and streamflow prediction based on meteorological input data [4].

Hydrological models are simplified, conceptual representation of hydrological cycle. Hydrological models have been used by hydrologists for the comprehension of hydrologic processes including simulation and estimation of hydrologic unknowns such as catchment flows for many decades. Hydrological models can be classified as either deterministic or stochastic. These models are often classified lumped, distributed and semi distributed model. Moreover, hydrological models can be evaluated under three titles: statistical models also known parametric or empirical models, conceptual models and physically based models. Physically based models are based on mass-energy balance and have physical meaning [5]. On the other hand, conceptual models are mainly based on mass conservation in association with simplified representation of momentum and energy equations. Both physically based and conceptual models require parameters associated with the basin characteristics which are not always available particularly for study regions in developing countries. In addition, complicated mathematical interactions, large amount of calibration data, overparameterisation effects and parameter redundancy impacts are the drawbacks of physically based and conceptual models. Hence, it is reasonable to apply alternative tools which can model relation between input and output data set without absolute physical meaning. Artificial Neural Networks (ANNs) can be used as an alternative modelling tool to physically based and conceptual models.

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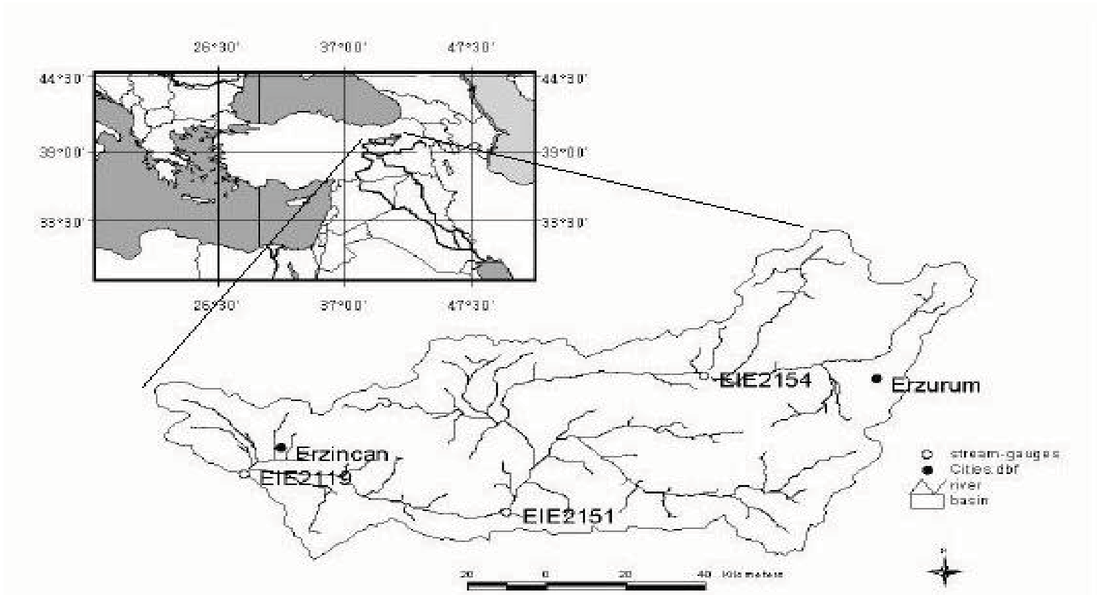


Fig. 1: Location map of Karasu Basin [29]

ANNs are flexible mathematical structure with the ability of defining sophisticated nonlinear relationship between input and output parameters without a need to solve complex partial differential equations. As a black box model, ANNs can be evaluated under empirical hydrological models title. ANNs were introduced to literature early 1940s by McCulloch and Pitts while trying to understand human brain and emulate its working processes mathematically. However, ANNs have gained attraction after characteristic details of computational processes were explained by [6]. Learning process of ANNs were presented by [7, 8]. Idea behind improving ANNs is simply developing a tool that can adapt itself changes in its environment for the purpose of solving nonlinear problems [9]. ANNs provide advantages over conventional hydrological models on successful identification of nonlinear hydrologic relationship between input output parameters, adaptation capability to changing circumstances, improved model performance, shorter calculation times with faster model development.

Due to several advantages of ANNs mentioned above, ANNs have been widely used in hydrological applications during last two decades. ANNs have been used for rainfall runoff modelling by [10-14,1] for streamflow forecasting by [15-17, 3]; for ground water modelling by [18-21]; for water quality modelling by [22,23]; for precipitation forecasting by [24-27]; and for sediment prediction by [28].

This paper presents implementation of ANNs method for forecasting catchment flows in a snow dominated mountainous basin named Karasu Basin, which is the headwater of Euphrates Basin. Very few of the past ANNs based flow forecasting studies considered snow related phenomena. In Karasu Basin, majority of the flow consists of snow melting. Prediction of catchment flow in Karasu Basin has got a high significance. However, so far there are only a few flow forecasting studies done on Euphrates Basin and its subbasins [29, 30]. So, effective data set on snow melting was determined from available literatures and they were integrated into ANNs based flow forecasting model. Moreover, ANNs based model results were compared with two lumped conceptual models which are using temperature index approach to calculate snow melt process, The Hydrologic Engineering Center- Hydrologic Modeling System (HEC-HMS) and Large Basin Runoff Model (LBRM). The main reason for selecting these models was relevant data availability for the study area.

Study Area and Data: Euphrates River originated from the mountainous Eastern Anatolia in Turkey, is one of the major rivers within Middle Eastern countries including Turkey, Syria and Iraq. Snow is the main water source of Euphrates Basin, particularly for Upper Euphrates Basin, which is also called Karasu Basin. High amount of Karasu Basin annual flow consists of snow melt runoff. Geographical location of Karasu Basin is longitudes from 38° 58'013''E to 41°38'28'' E and latitudes from 39°23'18'' N to 40° 24'26'' N. Basin location in Turkey is shown in Figure 1. Karasu Basin has an area of 10215 km^2.

It is the most mountainous part of Euphrates Basin with elevation range from 1125 m to 3487 m.

In Euphrates Basin, daily meteorological data including rainfall, minimum-maximum & average air temperatures, wind speed and humidity is available between 1 January 1975 and 31 December 2008. Moreover, station 2119, which is at the outlet of Karasu Basin provides daily flow data for the study. Flow data is available from 1 October 1975 to 30 September 1987 and between 1 October 1994 and 31 December 2004. Flow data is not available between 1 October 1987 and 30 September 1994 as the station 2119 was closed. Therefore, for the current study, common data period for the meteorology and flow data is from 1 October 1975 to 30 September 1987 and from1 October 1994 to 31 December 2004.

In Karasu Basin, minimum air temperature between 1975 and 2008 was -30°C while maximum temperature was 28.3°C. Observed average air temperature was 5°C. Maximum rainfall measured between 1975 and 2008 is 59.6 mm observed on 23 February, 2004. Furthermore, wind speed values were between 0 and 13.7 m/s, while relative humidity was ranging from 7 to 99.3. Moreover, Karasu Basin streamflows varied between 12.3 and 734 m^3/s. Maximum streamflow values were observed in spring seasons, when snow starts melting.

Data set was divided into training and test parts for the purpose of ANN model application. The test part is similar to validation process in conventional hydrological modelling. Data from 1 October 1975 to 30 September 1987 was selected as training data and from 1 October 1994 to 31 December 2004 was selected as test data.

MATERIALS AND METHODS

Artificial Neural Networks: ANNs are relatively new nonlinear statistical approach which has the capability to model complex nonlinear hydrological processes without physical expression. It is an alternative modelling approach that is inspired by brain and nervous systems. Fundamental theories of ANNs are the massive interconnections and parallel processing architecture of biological neuron systems [16].

ANNs can be defined as a network of interconnected neurons, also referred to as nodes, units or cells. Information processing is performed by nodes. Signals are transmitted between nodes by connection links. Connection strength of each link is explained with associated weight. For the purpose of determining each node's output signal, an activation function which is nonlinear transformation is implemented [31].

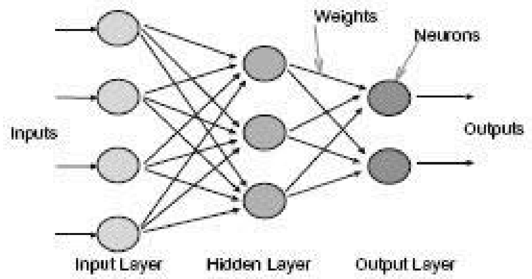


Fig. 2: Feed-forward network architecture [3]

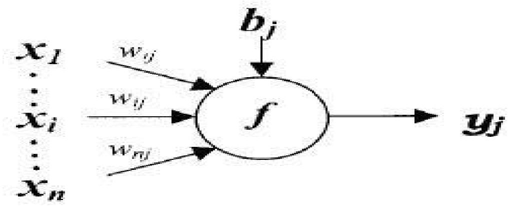


Fig. 3: Schematic diagram of single node [31]

A neural network is designed according to its architecture that consists of nodes, their connection weights and an activation function. The nodes in neighbouring layers are connected each other with links referred to synaptic weight that explains connection strength between nodes. Figure 2 schematically illustrates feed-forward neural networks.

Mathematical aspect of ANNs can be defined on a sample single neuron named j as follows. Figure 3 is schematic illustration of node j. The inputs coming to node j comprise input vector $X= (x_1,...,x_i,.....,x_n)$ in ANN. Similarly, group of weights coming to node j form weight vector $W=(W_{1j},....,W_{ij},...W_{nj})$. Weight vector, W_{ij} corresponds to a connection weight between i and j nodes. The effective incoming signal to node j is sum of all incoming signals and bias. Node j output, y_j is acquired by calculating the value of activation function, f, which determines the response of node to the effective incoming signal receiving to node j in terms of input vector, weight vector and bias of node j [31]. Following equation explains the mentioned process.

$$y_j = f(X\ W_j - b_j) \tag{1}$$

Non-linearity is provided by activation function in ANNs. The mostly used activation functions in literature are linear, sigmoid and hyperbolic tangent functions [15]. Among these three, sigmoid function is the most commonly used [16]. Sigmoid function is a bounded, monotonically increasing continuous function as shown below.

$$f(S_j) = \frac{i}{1+e^{-S_j}} \qquad (2)$$

Training process is performed by adjusting weights that connects nodes in a neural network. Some part of data set is split for training purpose. This is a similar process, which is called calibration in hydrological models. Training is a repeating process that consists of number of epochs until the underlying function is learned [32]. Primary aim of training is to minimize error function by adjusting ANN network connection weights and threshold values or bias with a continuous stimulation process. Error function is minimized by generating equal or closer network outputs to targets.

The Hydrologic Engineering Center- Hydrologic Modeling System: The Hydrologic Engineering Center- Hydrologic Modeling System (HEC-HMS) was originally developed to simulate the precipitation-runoff processes of dendritic watershed systems. Later, it was improved to solve significant hydrological problems including large river basin water supply, flood hydrology and small urban or natural watershed runoff [33]. There are three main components of HEC-HMS: basin component, meteorology component and control specification component.

Large Basin Runoff Model: The Large Basin Runoff Model (LBRM) was developed by the National Oceanic and Atmospheric Administration (NOAA)'s Great Lakes Environmental Research Laboratory (GLERL) in the 1980s to perform hydrologic simulations and water resources applications in the Great Lakes Basin. LBRM has been implemented to basins draining into the Laurentian Great Lakes for the purpose of simulation and forecasting runoffs [34, 35].

The LBRM is based on serial and parallel cascade of linear reservoirs (outflows proportional to storage) to represent moisture storages within a watershed: surface, upper soil zone (USZ), lower soil zone (LSZ) and groundwater zone (GZ) [35]. Total available heat is calculated by model each day, indexed by daily air temperature, to become potential evapotranspiration (ETP) or actual evapotranspiration (ET), a complementary approach. Model divides available heat between potential evapotranspiration and actual evapotranspiration according to total available heat. Model takes ET as proportional both ETP and storage. The model utilizes variable-area infiltration (infiltration proportional to the unsaturated fraction of USZ), daily precipitation and degree-day snowmelt [35].

RESULTS AND DISCUSSION

ANN Application in Karasu Basin: Suitable data selection is one of the most important issues for successful ANN model application. Suitable data set means sufficient data to achieve meaningful ANN model results. As it is stated before, Upper Euphrates Basin-Karasu Basin is a snow dominated area. Peak flows during a year are seen at the end of spring and beginning of summer seasons due to snow melt. Seasonal variation of flows is shown in Figure 4 for a sample year, 1995.

A reasonable set of snow ground data is not available in Turkey. Although some snow depth data are available for study basin, it is not sufficient for use in hydrological model. Thus, it is aimed to model snow runoffs using precipitation, air temperature, humidity, wind speed and temperature range data.

There are three most significant energy fluxes in the physics of snow melt; these are shortwave radiation, longwave radiation and turbulent fluxes including sensible and latent heat fluxes. [36] claimed that it is possible to explain physics of snow accumulation and melt with input data set involving precipitation, air temperature, wind speed, humidity and temperature range. Utah Energy Balance Model [36] has been developed based on this data set.

In addition, four different ANN models in terms of different input data set were generated and simulated. It is found that based on linear regression criteria precipitation, air temperature, humidity, wind speed and temperature range is the best input data set to simulate Karasu Basin runoffs.

It is important to standardize data to provide equal attention during the training process in successful ANN application. If data is not standardized, input variables in different scales will dominate training to a greater or lesser extent due to randomization of initial weights within a network to the same finite range.

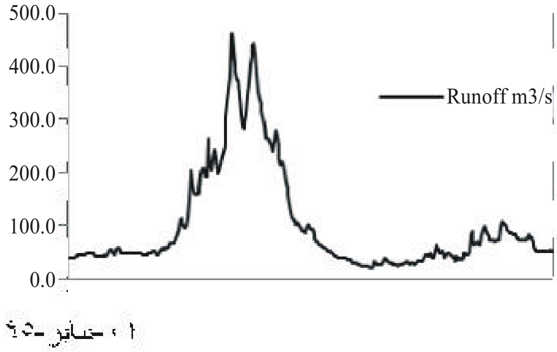


Fig. 4: Runoff graph in Karasu Basin in 1995

Table 1: Summary of different annual ANN runoff models

	Input Set	Output	Linear Regression (R)
Model 1	Precipitation(mm)+Air Temperature (ºC)	Flow (m^3/s)	Training: 0.59 Test: 0.51
Model 2	Precipitation (mm)+Air Temperature (ºC) +Humidity (%)	Flow (m^3/s)	Training: 0.65 Test: 0.51
Model 3	Precipitation (mm)+Air Temperature (ºC)+ Humidity (%)+Wind Speed (m/s)	Flow (m^3/s)	Training: 0.67 Test: 0.52
Model 4	Precipitation (mm)+Air Temperature (ºC)+Humidity (%)+Wind Speed (m/s)+Temperature Range (ºC)	Flow (m^3/s)	Training: 0.78 Test: 0.52

Moreover, it is significant to standardize data for the efficiency of training algorithms (Dawson & Wilby, 2001). Thus, all data set was standardized into [0-1] range by using following equation.

$$X=\frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3}$$

In Equation 3, X refers to standardized data where X_{min} and X_{max} are minimum and maximum values of any particular data.

Feed Forward Back Propagation (FFBP) algorithm is obviously most popular training algorithm for ANN based hydrological studies. Thus, FFBP was selected as a training algorithm for the current study. Due to widespread usage of Multilayer Perceptron (MLP) ANN network type in hydrology studies, it is decided to use MLP as ANN network type in this study.

Furthermore, it is very significant to consider seasonality in Karasu Basin to achieve a better application of ANN based runoff model. Major portion of runoffs consist of snow melt and peak flows are seen late spring and early summer periods. Thus, it is also necessary to perform seasonal analysis using only spring and summer periods. So, ANN model in Karasu Basin was developed and run for both annual (whole year) and seasonal (Spring -Summer) periods.

Annual ANN Model: Four different models (Model 1, Model 2, Model 3, Model 4) were generated to simulate daily Karasu Basin runoffs for whole year using different input data sets. First model uses precipitation and air temperature to model runoffs while the last one uses precipitation, air temperature, humidity, wind speed and temperature range to simulate runoffs. Model 4 showed the best performance with a linear regression coefficient (R) of 0.78 for training phase and 0.52 for test phase. The first model showed worst performance with a linear regression coefficient of 0.59 for training phase and 0.51 for test phase. Summary of different ANN model outcomes are presented in Table 1.

Number of hidden layers was decided as 5 and number of neurons in each hidden layer was selected as 10 based on trial-error procedure in ANN models. Flow scatter diagrams of best ANN model (Model 4) are shown in Figure 5.

Moreover, comparison of observed and modelled flow time series graphs at the outlet of Karasu Basin for training and test phases are shown in Figure 6.

Model performance was evaluated in terms of one of the most popular assessment criteria in hydrological studies named Nash Sutcliffe coefficient of determination (R^2) as defined in Equation 4.

$$R^2 = \frac{\sum(Q_{obs} - Q_{mod})^2}{\sum(Q_{obs} - \overline{Q_{obs}})^2} \tag{4}$$

In eguation 4, Q_{obs} corresponds to observed flow where Q_{mod} corresponds to modelled flow. Moreover, $\overline{Q_{obs}}$ refers to mean observed flow. R^2 for training and test phases was found 0.71 and 0.50 respectively. Model performance is not very good because of impacts of large variations in seasonal flows.

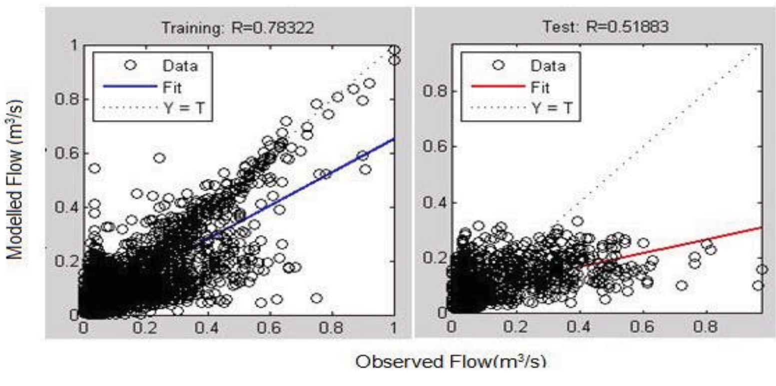
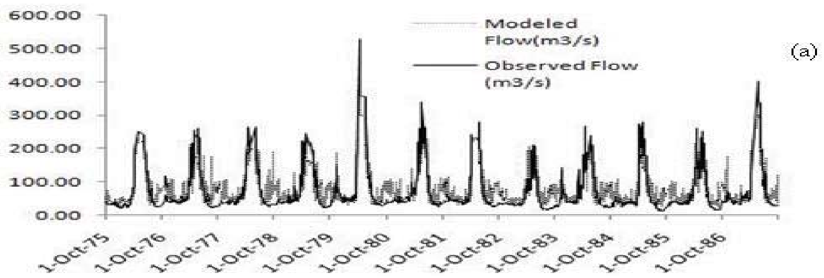


Fig. 5: Flow scatter diagrams of training and test phases in annual analysis



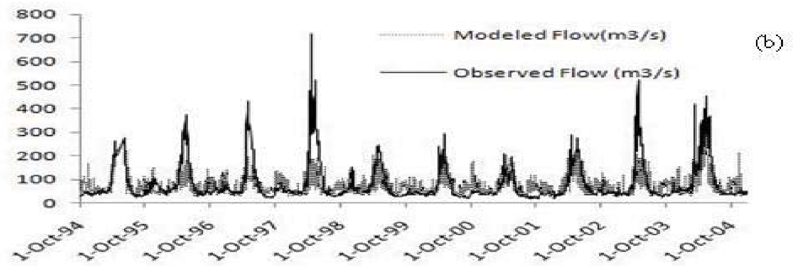


Fig. 6a-b: a: Observed-Modelled flow graph at Karasu Basin outlet point for training phase
b: Observed-Modelled flow graph at Karasu Basin outlet point for test phase

Table2: Different seasonal ANN runoff models

	Input Set	Output	Linear Regression (R)
Model 1	Precipitation (mm)+Air Temperature (ºC)	Flow (m^3/s)	Training: 0.74 Test: 0.65
Model 2	Precipitation (mm)+Air Temperature (ºC) +Humidity (%)	Flow (m^3/s)	Training: 0.78 Test: 0.68
Model 3	Precipitation (mm)+Air Temperature (ºC)+Humidity (%)+Wind Speed (m/s)	Flow (m^3/s)	Training: 0.78 Test: 0.68
Model 4	Precipitation (mm)+Air Temperature (ºC)+Humidity (%)+Wind Speed (m/s)+Temperature Range (ºC)	Flow (m^3/s)	Training: 0.88 Test: 0.71

Other than snowmelt season, flow consists of baseflow and limited amount of rainfall. With the start of snowmelt, flow increases significantly. Large variations between low flows and peak flows is the cause of ANNs incapability to simulate to such a large variations.

Seasonal ANN Model: Daily meteorological data between 1976 and 2004 was used to develop seasonal ANN models. Unlike annual model, meteorological and flow data between March and August months were used for the purpose of developing seasonal models. Similar to annual model, four models according to different input set were generated and comparisons between observed and modelled flows were assessed through linear regression. Model details and performances based on linear regression are shown in Table 2.

As it can be seen in Table 2, best model performance was obtained for Model 4 with a linear regression coefficient of 0.88 for training phase and 0.71 for test phase. It means precipitation, air temperature, humidity, wind speed and temperature range is the best input data set to simulate flows in Karasu Basin. Worst performance was observed for Model 1, however still it is not very bad and may be acceptable to simulate runoffs in Karasu Basin.

Analogous to annual model, feed forward back propagation learning algorithm was used for seasonal model application. Different numbers of neurons and hidden layers were experienced in this case. As a result, 5 hidden layers with 10 neurons each provided the best results and used in seasonal ANN models. Flow scatter diagrams of training and test phases for Model 4 are shown in Figure 7.

Model performance is also evaluated in regards to Nash-Sutcliffe coefficient of determination (R^2). R^2 is calculated as 0.81 for training phase and 0.70 for test phase for Model 4. Comparison of modelled and observed flow time series graphs at the outlet of Karasu Basin are shown in Figure 8 for training and test phases.

It is to be noted that Figures 8 (a) and (b) are the comparisons of observed flow and modelled for March-August periods only.

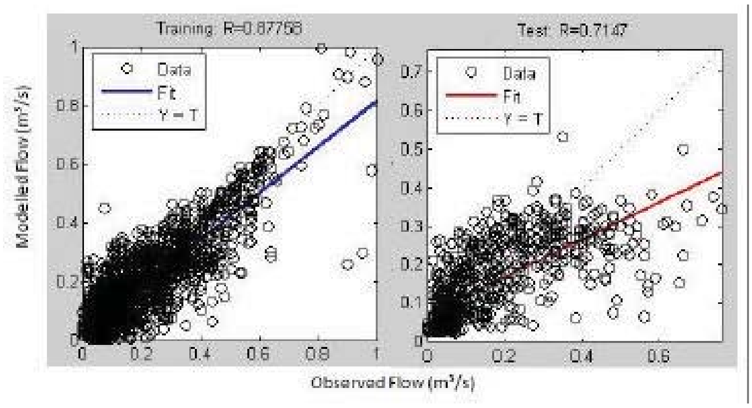


Fig. 7: Seasonal flow scatter diagrams of training and test phases in seasonal analysis

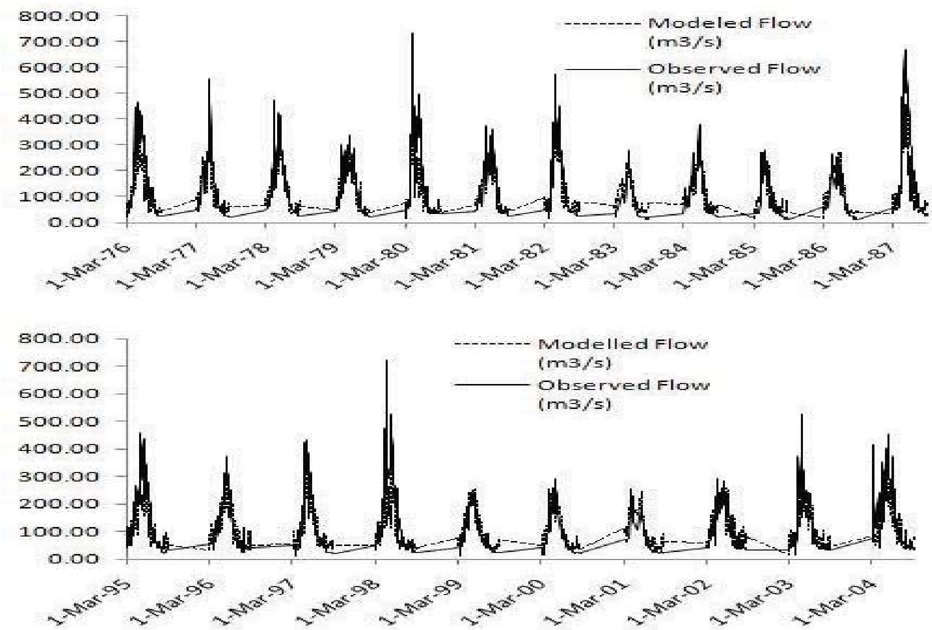


Fig. 8a-b: a: Seasonal observed-modelled flow graphs for training phase
b: Seasonal observed-modelled flow graphs for test phase

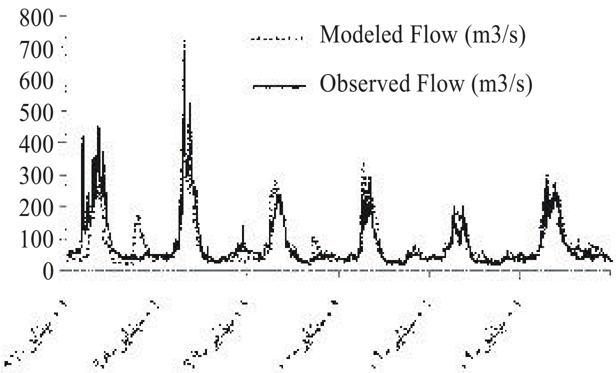


Fig. 9: HEC-HMS comparison hydrograph for calibration run at outlet point of Karasu Basin

Table3: Calibration run performance in HEC-HMS

	1997-2002 Calibration Run
Nash-Sutcliffe Coefficient of Determination	0.70
Linear Regression	0.70

Table 4: Validation run performance in HEC-HMS

	2003-2004 Validation Run
Nash-Sutcliffe Coefficient of Determination	0.76
Linear Regression	0.77

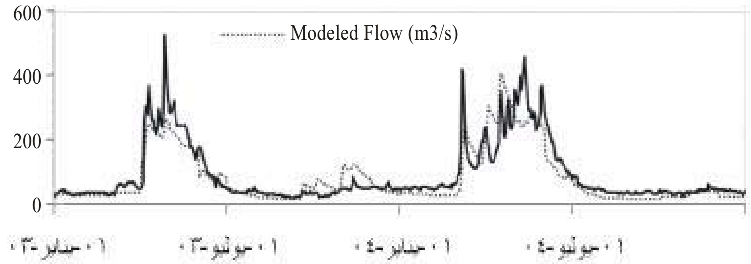


Fig. 10: HEC-HMS comparison hydrograph for validation run at outlet point of Karasu Basin

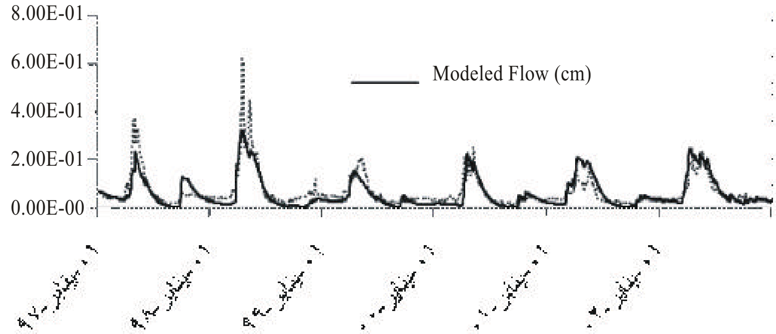


Fig. 11: LBRM comparison hydrograph for calibration run at outlet point of Karasu Basin

HEC-HMS Application in Karasu Basin: HEC-HMS model was applied to Karasu Basin in lumped structure at daily time step. For study area, model was run between 1997 and 2004. Calibration was performed from 1 January, 1997 to 31 December, 2002. By using calibration trial, it is possible to calibrate basin component parameters including loss, transform, baseflow and routing methods. However, there is no option to calibrate meteorological component parameters in HEC-HMS. Comparison hydrograph of modeled and observed outflow at basin outlet after calibration run is shown in Figure 9.

Calibration period model performance was evaluated in terms of Nash-Sutcliffe coefficient of determination (R^2) and linear regression coefficient. Performance evaluation results are shown in Table 3.

Validation process was accomplished between 1 January, 2003 and 31 December, 2004. Basin outlet point flow comparison hydrograph for validation run is demonstrated in Figure 10. Validation run results according to Nash-Sutcliffe coefficient of determination and linear regression coefficient are shown in Table 4.

According to performance assessment results, it is possible to state that HEC-HMS model has an adequate accuracy to simulate runoffs in Karasu Basin.

LBRM Application in Karasu Basin: The LBRM was applied to Karasu Basin at daily time step and calibration run was performed from 1 January, 1997 to 31 December, 2002 similar to HEC-HMS application. Comparison hydrograph of outlet outflow is shown in Figure 11.

Calibration run model performance was evaluated according to Nash-Sutcliffe coefficient of determination and linear regression. Moreover, validation was performed between 1 January, 2003 and 31 December, 2004. Results are shown in Table 5 (a) and (b).

Table 5: (a) Calibration run performance in LBRM (b) Validation run performance in LBRM

(a)	1997-2002 Calibration Run
Nash-Sutcliffe Coefficient of Determination	0.73
Linear Regression	0.75
(b)	2003-2004 Validation Run
Nash-Sutcliffe Coefficient of Determination	0.72
Linear Regression	0.75

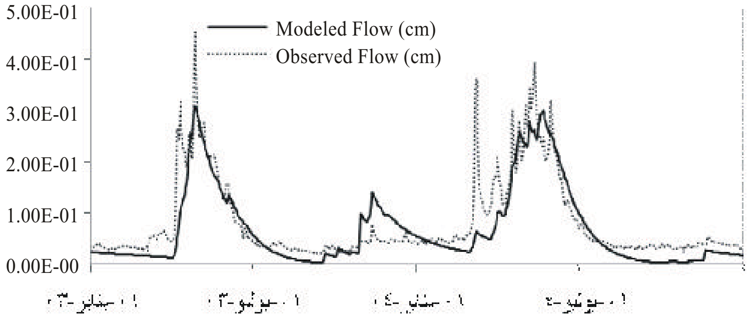


Fig. 12: LBRM comparison hydrograph for validation run at outlet point of Karasu Basin

Furthermore, flow hydrograph at basin outlet is shown in Figure 12.

In terms of Nash Sutcliffe coefficient of determination and linear regression, it can be concluded that LBRM has an adequate ability to simulate runoffs in Karasu Basin.

CONCLUSIONS

It was aimed to simulate streamflows of Upper Euphrates Basin using current popular method in hydrology named Artificial Neural Networks. Artificial Neural Networks was selected owing to its capability to model non-linear hydrological processes successfully. Moreover, use of ANN does not require high expertise on in-depth hydrological processes. Finally, ANN has relatively low computational demands and it is possible to integrate it with other mathematical tools easily.

Most of the previous studies with ANN hydrological simulations dealt with rainfall contributed runoff simulations only. It is more difficult to simulate runoff process in snow dominated basin in compared to runoff process in rainfall dominated basin. Because, for snow dominated basin both runoffs from rainfall and snow melt need to be considered. Moreover, physical processes of snow accumulating and melting are highly complex, including mass and energy balances as well as heat and mass transport by conduction, vapour diffusion and meltwater drainage (Tarbaton & Luce, 1996).

To find most suitable results, it is important to select correct input data set to simulate snow melt successfully. Different combinations of input data sets among precipitation, air temperature, temperature range, humidity and wind speed data were used to explore best input data set. Four different ANN models were developed based on different input data set for both annual and seasonal analyses. It is found that for both annual and seasonal analyses, Model 4 showed the best performance to simulate runoffs in Karasu Basin. For Model 4, input data set consists of precipitation, air temperature, humidity, wind speed and temperature range. However, due to the drawback of ANN to find global optima in complex parameter spaces, performances of models are not too high but good enough. Because of ANN's incapability to simulate large variations, both low flows and peak flows were not matched to expected accuracy. To overcome this issue, a seasonal analysis and modelling was performed with only peak-flow season (spring-summer) data.

It is found that the ANN model is sensitive to season simulations. Seasonal runoff simulations involving data between March and August were run in addition to annual (whole year) simulations. It is found that model performances increased significantly for seasonal simulation compared to annual simulations. For Model 4, linear regression coefficient increased from 0.78 to 0.88 for training phase and increased from 0.52 to 0.71 for test phase. Also, Nash-Sutcliffe coefficient of determination was increased significantly. For training phase it increased from 0.71 to 0.81 and for test phase increased from 0.50 to 0.70.

Although ANN model is evaluated based on Nash-Sutcliffe coefficient of determination and linear regression, comparing ANN model results with HEC-HMS and LBRM results is useful to determine the performance of ANN model. HEC-HMS and LBRM results are more successful than annual ANN models in both calibration (training) and validation (test) periods. However, seasonal ANN model with best performance (Model 4) is more successful than HEC-HMS and LBRM in calibration period, while HEC-HMS and LBRM results are slightly more achievable than best ANN model (Model 4) in validation phase.

On the other hand, calibration and validation periods of ANN models are larger than HEC-HMS and LBRM. If this period is reduced, ANN model performance will probably show a slight decrease. For instance, R^2 would be 0.66 (currently 0.70) in Model 4, if validation period is shorten from current time slice (1994-2004) to same period with HEC-HMS and LBRM (2003-2004).

In summarize, seasonal ANN model with input data including precipitation, air temperature, humidity, wind speed and temperature showed adequate performance to simulate snow runoffs. Advantages of ANN models over conventional hydrological models were discussed before. Results of study demonstrated that most important advantage of ANN model over HEC-HMS and LBRM in snow dominated basin was shorter calculation times with faster model development. Moreover, ANN is a black box model based on relation between input and output data. So, it does not require large experience on hydrology for model application. On the other hand, input data requirement of ANN model to simulate snow melt runoffs is larger than HEC-HMS and LBRM. However, it is still using basic meteorological data.

Finally, ANN model performance to simulate snow runoffs is good enough especially when considering spring - summer periods, which are in fact most important seasons in terms of runoff volumes. As a further step, it is recommended to use snow data such as snow depth or snow water equivalent as input data with other compatible inputs. It will most likely increase model performance in estimating snow runoffs from snow dominating basins.

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