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Comparison of different rainfall-runoff models performance: A case study of Liqvan catchment, Iran

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Abstract: A vast part of Iran is located in arid and semiarid areas. In these localities, rainfall is typically meagre, irregular and highly variable. The precipitation variability in these areas causes uncertainties in runoff prediction. The mutual interaction between the climatic parameters including temperature, precipitation, evaporation, wind and etc. and hydrological factors like streamflow, concentration time, permeation and others has rendered the relationship between rainfall and runoff take a nonlinear and undetermined form. The objective of the present study is the simulation rainfall-runoff process via taking advantage of two conceptual models, namely HEC-HMS and IHACRES and three other empirical approaches models Including Artificial Neural Network (ANN), Multiple Linear Regression (MLR) and Simple Linear Regression (SLR); moreover, The models' performance has also been compared regarding the Liqvan River in Iran. Monthly time series data of Streamflow and Meteorological data were applied for the duration of 1972 to 2004. The R^2, RMSE, Te and MAE indices are used to achieve desired model. IHACRES model showed a desirable performance in estimating the normal streamflow but the peak streamflows are overestimated. Similar to IHACRES, HEC-HMS model does not makes adequate performance in estimating the peak streamflows despite the fact that the HEC-HMS overall performance was better. MLR model could simulate the normal flow but peak streamflows are underestimated. Due to the simplicity of the SLR model, its simulation performance was unacceptable. ANN model provides more appropriate estimations in terms of peak streamflows in comparison to the other models. Also In total, the results of the evaluation showed that the ANN model was more accurate (R^2 = 0.80, RMSE = 0.29, Te = 0.004, MAE = 0.003).

Key words: Rainfall-Runoff Simulation, Artificial Neural Network, HEC-HMS, IHACRES, Liqvan Catchment

1. INTRODUCTION

A vast part of Iran is located in arid and semiarid areas. In these localities, rainfall is typically meager, irregular and highly variable (Ahrens, 2003). The precipitation variability in these areas causes uncertainties in runoff prediction. In practice, the complex models often do not provide more accurate runoff predictions relative to simpler and less detailed ones (Bahat et al., 2009).

Estimating catchment streamflow is of a great importance because the deficiency in streamflow can lead to financial losses and its excess, in the form of flood, can cause financial as well as life losses. The necessity to appropriately predict the river flows in engineering constructions, river management, the surface water reservoir management and flood warning systems is tangibly felt. Also, the simulation of the river flows for the purpose of getting aware of the prospective river flow rates are among the significant and applied issues in water resources management (Fathabadi et al., 2009).

The mutual interaction between the climatic parameters including temperature, precipitation, evaporation, wind and etc. and hydrological factors like streamflow, concentration time, permeation and others has rendered the relationship between rainfall and runoff take a nonlinear and undetermined form. The objective of the present study is the simulation rainfall-runoff process via taking advantage of two conceptual models, namely HEC-HMS and IHACRES and three other empirical approaches models Artificial Neural Network (ANN), Multiple Linear Regression (MLR) and Simple Linear Regression (SLR); moreover, The models' performance has also been compared

regarding the Liqvan River in Iran.

There are numerous studies performed in relation to the rainfall-runoff process simulation as well as various methods comparisons. Lallahem and Mania (2002) offered an appropriate method based on artificial neural network for large-scale problems and longtime intervals and compared theirs with the other methods. Dastorani et al. (2009) made use of artificial neural network along with other models for rebuilding the current discharge data and they concluded the superiority of the neural network results in comparison to the correlation and normal ratio methods. Asati and Rathore (2012) developed an autoregressive model, MLR and ANN for a complex non-linear relationship between rainfall as input data and output as runoff, without considering the nature of process and compared the performance of each model. Yaghoubi and Massah Bavani (2014) compared three models of HVB, HEC-HMS and IHACRES in A'azam Harat catchment in Iran. HVB model proved to be displaying the best performance and HEC-HMS exhibited the lowest performance.

2. MATERIALS AND METHODS

2.1 Study area

Liqvan Catchment, with an area of 76 km^2, is located in the southern section of the city of Tabriz in Iran and it originates from the northern foothill of Sahand Mountain. It continues its route towards north after joining the tributary branches and, as the main drainage system of the catchment, finally, discharges to AjiChai River. Geographically, it is located in 38º,01′,30′′ to 37º,43′,30′′ of the Northern latitude and 46º,31′,3′′ to 46º,22′,00′′ of the Eastern latitude. The position of Liqvan catchment and also Liqvan station has been shown in Figure 1.

Liqvan Catchment has a dry and cold climate. The catchment height reaches to an average value of 2675 meters and its average annual precipitation is 318 mm. The slope is 25 percent on average and the main waterway expose a slope of 9 percent. Geologically, the Floor and sides of the river bed are made of tuffs and according to the characteristic features of such material the waterway basin shows low permeability.

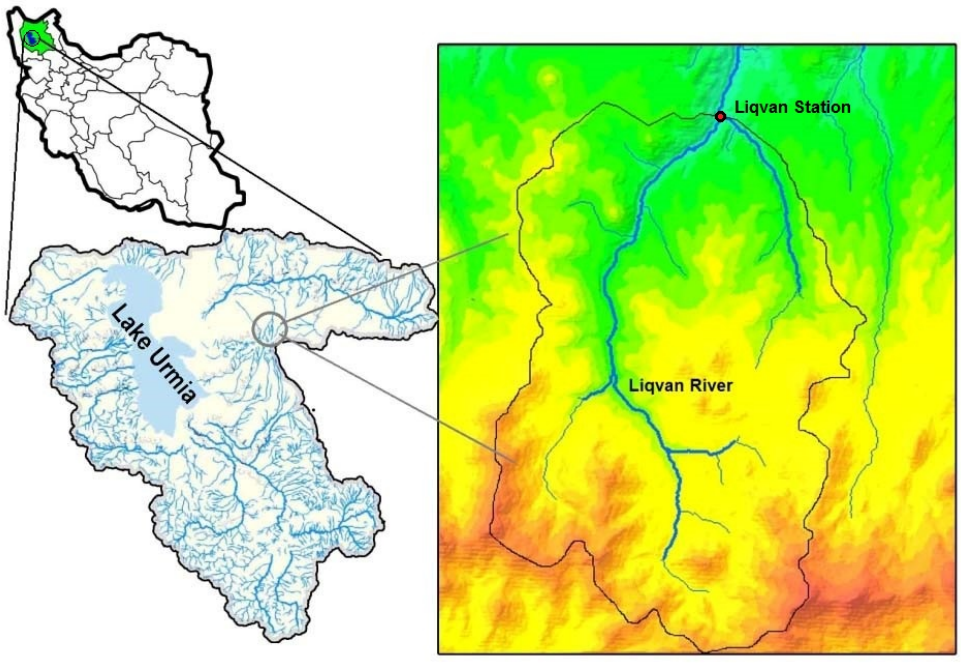

Figure 1. General location of Study Area.

2.2 IHACRES

IHACRES is an integrated metric-conceptual model for the simulation of the precipitation-runoff (Jakeman et al., 1990). IHACRES model is applied for the simulation of the runoff in catchments for which the precipitation and temperature data have been recorded incessantly. The model, as observed in Figure 2, is consisted of two nonlinear and linear associated parts which are, respectively, used to calculate the losses and transform the effective precipitation to runoff.

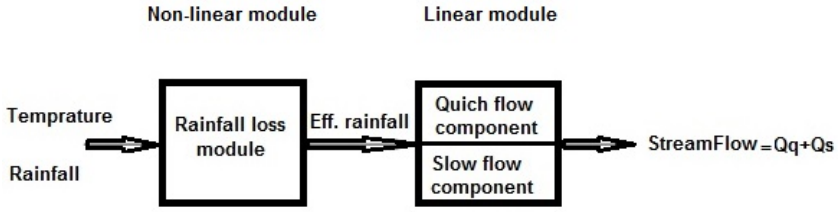

Figure 2. Linear, nonlinear and the output part of IHACRES model.

2.3 HEC-HMS

HEC-HMS (The Hydrologic Engineering Center - the Hydrologic Modeling System) is a physically based distributed model, designed to simulate the rainfall-runoff processes of dendritic catchment systems. The model is capable of simulating the catchment in accordance with various climatic conditions. HEC-HMS model takes hydrological elements such as catchment boundaries, sub-catchment and etc**.**, the waterways connection points and drainage points as its inputs and it requires climate data, soil type, vegetative cover and casualties in every sub-catchments (Scharffenberg and Fleming, 2010). HEC-HMS includes three main components: Basin model, Meteorological model, and Control specifications. The basin model stores the physical datasets describing the basin properties and the meteorological model includes precipitation, evapotranspiration, and snowmelt data. The time span of a simulation is controlled by control specifications including a starting date and time, ending date and time, and computation time step (Anderson et al., 2002).

In the present study, SCS-CN method has been used for modeling the intensity of losses. In Figure 3, the land use map for Liqvan sub-catchments was determined by taking advantage of Landsat satellite images from July 2004. Then, ArcHydro toolbox was applied to delineate the Curve Number (CN) map by making use of soil specifications and land use map of study area.

2.4 Artificial Neural Network

Artificial Neural Networks (ANN) is a simple model of human's brain. An ANN is nonlinear mathematical structure that has ability to show the nonlinearity process for communicating between inputs and outputs of any system. This network is training with present data in learning process and can be used for future prediction. Each network has been formed from one input layer, one output layer and one or more hidden layer. Neurons of each layer are connected to next layer by weights (Akbarpour and Rahnama, 2006).

2.5 Multiple Linear Regression

Regression analyses are among the oldest statistical techniques used in hydrology. Multiple Linear Regressions (MLP) represent a mathematical equation expressing one random variable as being correlatively related to another random variable, or to several random variables. The regression equation may be any function that can be fitted to a set of points of observed variables

(Sobri et al., 2002). Regression analysis is a statistical technique for creating a linear relationship between the dependent and independent variables. It aims at predicting the dependent variable from the independent variable. Multivariate linear regression equation is as stated below:

$$Y_i = c_0 + \sum_{j=1}^{n} a_j X_{ij} \quad (1)$$

where, α is the regression parameters, X is the independent variables, c is the equation fixed constant and Y is the regression equation.

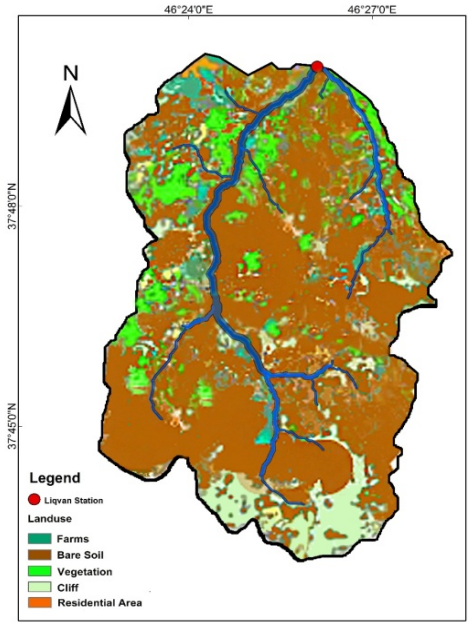

Figure 3. Land use map of the study area.

2.6 Simple Linear Regression

Linear Regression is the simplest regression model (SLR) which was frequently used in the past. In SLR model, the Equation below is applied to create a relationship between the dependent and independent variables.

$$y = Ax + B + \varepsilon \quad (2)$$

where, Y_i is the dependent variable and x is the independent variable and ε is the error.

2.7 Data Used in the Models

Monthly Streamflow and climate data from March 1972 through March 2004 were used from Liqvan station. Precipitation data (mm) and temperature data (ºC) are inserted as input variables for the runoff simulation and the streamflow (cubic meters per second) data are used for assessing IHACRES and ANN models accuracy. Also, wind speed, sun radiation, precipitation and temperature data were used for HEC-HMS and MLR models; In addition, the precipitation data was used in SLR model.

2.8 Performance Criteria

To achieve desired optimal model, correlation of determination (R^2), root mean square error

(RMSE), total error (T_e) and mean absolute error (MAE) are used in current study.

3. RESULTS

For IHACRES, simulation results in calibration stage are as presented in Table 1.

Table 1. IHACRES Calibrated coefficients.

C	τ_w	f	τ_{ref}	I	P
0.00093	7	3.5	2	0	1

To run HEC-HMS3.5, hydrological elements including catchment, sub-catchments and waterways network, waterways connection point and the model's output point were determined by making use of ArcHydro, and the sub-catchments characteristics are summarized in Table 2.

Table 2. Sub-catchments characteristics.

sub-basin	**1**	**2**	**3**	**4**
Slope (%)	12.3	8.4	7.0	4.0
Concentration time (hr)	25.5	36.4	47.6	64.8
Lag time (hr)	15.3	21.8	28.6	38.9

Land use map and soil specifications were used to generate the curve number map which is illustrated in Figure 4.

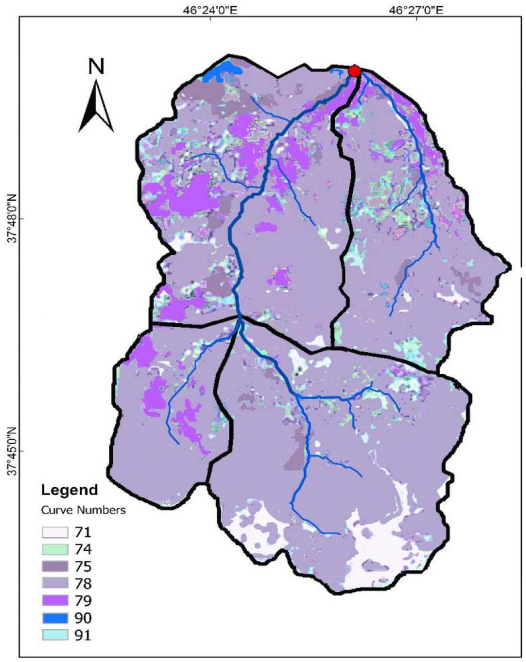

Figure 4. Liqvan catchment Curve Number map.

The generated Neural Network possesses two input layers due to having two inputs, namely precipitation and temperature. Ten neurons have been considered for the neural network and 25 years of data were applied for training and the remaining were used for testing. Also, the determination coefficients (R^2) for training, validation and test stages were 0.77, 0.94 and 0.73, respectively.

In MLR Model, According to the results obtained and also based on the finding that the minimum and maximum temperatures do not show a high correlation (Pierson's correlation coefficient approaching unity), daily mean temperature as well as a new parameter extracted

through multiplying maximum temperature by minimum temperature were applied (Tmm).

Based on the investigations performed on the three parameters, namely R^2, Cp and PRESS, and using two methods of ENTER and STEPWISE, the equation presented in Table 3 was accepted as the final equation. It's accepted, based on the fact that it offers the least values for Cp and PRESS and a maximum value for R^2 and also because its Durbin-Watson value was above 1 and it had VIFs below 10.

Table 3. Accepted equation of MLR model

Inputs	Equation	Press	Cp		VIF
P,T, R, Tmm	Q=-0.031+0.009·P+0.038·T+ 0.095·W+0.001·Tmm+0.003·R	121	6	P	1.2
				T	1.5
				W	2.6
				Tmm	6.6
				R	5.8

MLR Model validation was carried out for the years from 2002 to 2004 and the relative error value (RE) and RMSE were obtained 0.58 and 0.51, respectively which is indicative of a high error level of the model. According to the results obtained from SLR model simulations, PRESS was found 177 for this model which is indicative of a lack of optimum ability of the model for simulations. Figure 5 shows the determination coefficient (R^2) of observed and simulated values of each model. The evaluation performances of models have been summarized in the Table 4 and Figure 6 also exhibits the simulated and observed streamflow acquired by models.

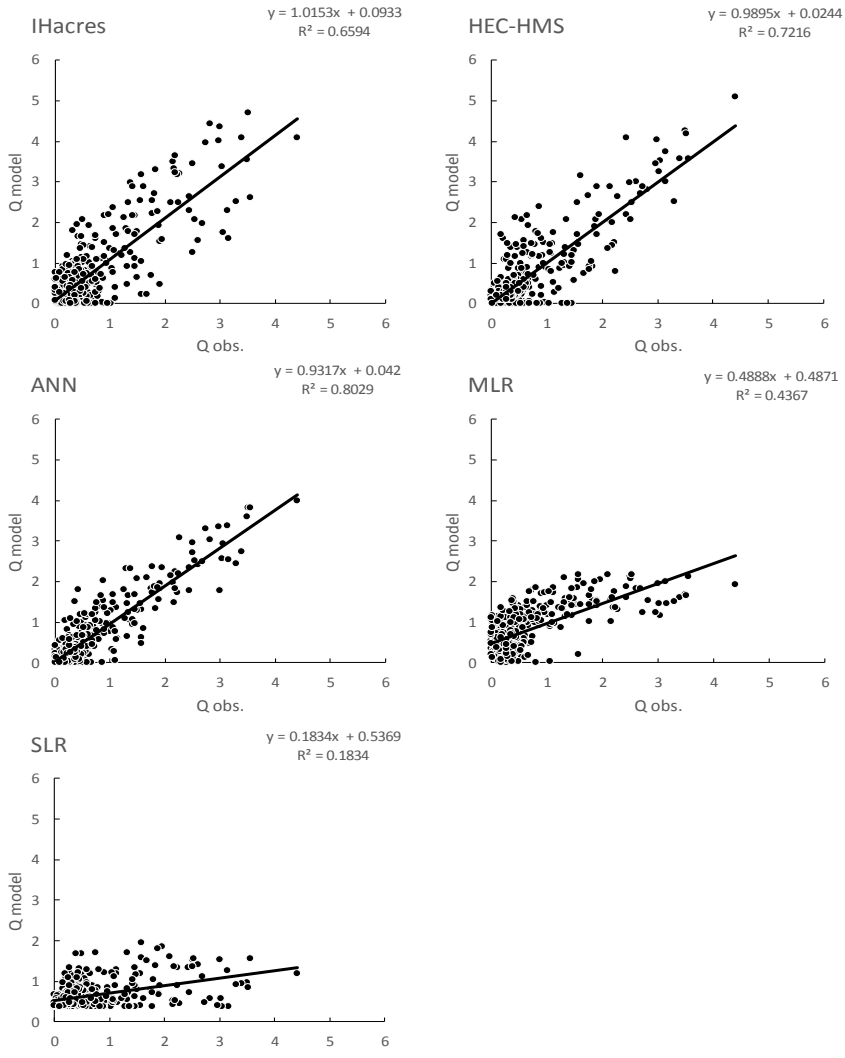

Figure 5. The determination coefficient of each model.

Table 4. Summarized models evaluation indices.

Model	RMSE	R^2	TE	MAE
ANN	0.29	0.80	0.004	0.003
HEC-HMS	0.41	0.72	0.026	0.017
IHACRES	0.43	0.66	0.157	0.103
MLR	0.57	0.45	0.229	0.430
SLR	0.44	0.18	0.022	0.450

Figure 6.The simulated and observed streamflow time series of models.

4. DISCUSSION AND CONCLUSIONS

According to Figure 6, it is evident that the IHACRES does not show a high competency in

simulating the peak streamflows. It displays a favorable performance in estimating the normal streamflow but as it is seen the peak streamflows are overestimated. Similar to IHACRES, HEC-HMS model does not makes adequate performance in estimating the peak streamflows despite the fact that the overall performance is better. ANN model provides more appropriate estimations in terms of peak streamflows in comparison to the other models and the shape of the simulated streamflow generally follows the observed streamflow. MLR model does not have the ability to simulate the peak streamflows and it shows better performance in simulating the normal streamflow. And as expected, SLR model is not suitable for simulating. SLR model leads to a severe underestimation of peak streamflows.

According to the Table 5, the highest determination coefficient goes to the neural network and it is indicative of the higher accuracy of the model output. This is because the neural network is trained based on the observed flow. Artificial Neural network model also indicates the lowest RMSE among the extant models which shows the ANN model is more accurate.

After ANN model, HEC-HMS exhibits the better performance. The weaknesses of HEC-HMS model can be explained as model considers fixed values for physical parameters regarding the various flood incidents during simulation period (Ia and CN). In other words, the change in the land use resulting from the human activities brings about an uncertainty in curve number (CN).

IHACRES model shows relatively promising results and its weakness is predominantly due to the complicacy of the climatic behavior. The low number of the parameters required by the model as inputs can be pointed out as the advantages of this model.

MLR model outperforms SLR model due to its taking more input parameters into consideration, though both of the models showed weaker performances in comparison to the other models because of considering the runoff behavior as linear.

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