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Long Lead Runoff Simulation Using Data Driven Models

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Abstract

Runoff simulation is a vital issue in water resource planning and management. Various models with different levels of accuracy and precision are developed for this purpose considering various prediction time scales. In this paper, two models of IHACRES (Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data) and ANN (Artificial Neural Network) models are developed and compared for long term runoff simulation in the south eastern part of Iran. These models have been utilized to simulate5-month runoff in the wet period of December-April. In IHACRES application, first the rainfall is predicted using climatic signals and then transformed to runoff. For this purpose, the daily precipitation is downscaled by two models of SDSM (Statistical Downscaling Model) and LARS-WG (Long Ashton Research Station-Weather Generator). The best results of these models are selected as IHACRES model input for simulating of runoff. In application of the ANN model, effective large scale signals of SLP(Sea Level Pressure), SST(Sea Surface Temperature), ΔSLP and runoff are considered as model inputs for the study region. The performances of the considered models in real time planning of water resources is evaluated by comparing simulated runoff with observed data and through SWSI(Surface Water Scarcity Index) drought index calculation. According to the results, the IHACRES model outperformed ANN in simulating runoff in the study area, and its results are more likely to be comparable with the observed values and therefore, could be employed with more certainty.

Keywords: *Downscaling, Long term runoff, Simulation, ANN, Large scale climate signals, IHACRES.*

1. Introduction

Runoff is the base component of water resources management. Water resources planning and management policies are developed by projection of runoff and demand variation schemes in a specific time horizon. In other words, long term runoff simulation provides an opportunity for decision makers and managers to develop the appropriate action plans to deal with extreme situations. Runoff has been widely applied for hydrologic drought analysis as well as flood simulation [1-3].

Numbers of empirical and theoretical methods have been developed for runoff simulation and prediction. The precision of the predicted values plays an important role in developing the appropriate plans in contingency situations such as droughts. Mathematical methods as well as ANN(Artificial Neural Network) have been widely applied in the modeling of hydrological processes, especially in recent decades. Researchers such as Coulibaly et al. have presented interesting applications of these models in hydrology although the need of long time series for the training of these models has limited their application in long term predictions [4]. Karamouz and Araghynejad have used the ANN model for hydrological modeling in integration with Fuzzy theory for long term prediction of Zayandeh-Rood river discharge [5]. Misaghi et al. used ANN to predict the tidal level fluctuations, which is an important parameter in maritime areas. A time lagged recurrent network (TLRN) was used to train the ANN model. Different model structures were used and compared with each other. In addition, an ARMA model was used to simulate time series data to compare the results with the ANN forecasts. Results proved that ANN can be used effectively in this field and satisfactory accuracy was found for the two examples [6]. Dastorani and Wright used ANN to optimize the results obtained from a hydrodynamic model of river flow prediction. Using ANN in this way, the error produced by the hydrodynamic model was predicted and thereby, the results of the model were improved [7].

Due to low resolution of GCMs (General Circulation Models) outputs, some downscaling techniques have emerged

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as means to obtain local-scale weather variables from regional-scale atmospheric predictor variables. Harpham and Wilby predicted the precipitation for different zones of England using different downscaling models such as SDSM (Statistical Downscaling Model) [8], radial neural networks (neural networks with kernel based functions) and multi layer perceptron neural networks [9]. The results of their investigation show that all of these models are capable of predicting precipitation in different regions, however their capabilities are different depending on the special characteristics of each region. MassahBavani used Kriging and the inverse weighting method for downscaling precipitation and temperature of the Zayandeh-rud basin in Iran. His results indicated that both of these methods are capable of downscaling precipitation and temperature [10]. Zahabiyoun downscaled GCM outputs, using regressions between atmospheric circulation indices (ACIs) and rainfall statistics. The relationships then used to predict the rainfall statistics for future conditions using GCM outputs [11].

A stochastic weather generator can however serve as a computationally inexpensive tool to produce multiple-year climate change scenarios at the daily time scale which incorporate changes in both mean climate and in climate variability [12]. LARS-WG(Long Ashton Research Station-Weather Generator) is a stochastic weather generator which can be used for the simulation of weather data at a single site, under both current and future climate conditions [13, 14 and 15]. These weather data are in the form of daily time-series for climate variables, namely, precipitation (mm), maximum and minimum temperature (°C), and solar radiation.

As runoff is the basic component of water resources management practices, many attempts has been made for runoff prediction.SeyedGhasemi et al. assessed climate change, by using GCM outputs as the input to a rainfall-runoff model named SWAT (Soil and Water Assessment Tool), in order to model the Zayandeh-Rud river streamflow[16].In this study, the performance of IHACRES (Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data)and ANN models in runoff simulation in the Ghasre-Ghand region in the Kajoo river basin, located in the south-western part of Iran, are compared. The most common hydrological drought index called Surface Water Supply Index (SWSI) [17] has been used in this study for evaluation of performance of the models. IHACRES model uses daily rainfall data for runoff simulation. Rainfall on a regional scale is simulated using GCM data by SDSM and LARS-WG models. For runoff simulation using ANNs, the predictors are selected among large scale climatic signals including SLP(Sea Level Pressure), SST (Sea Surface Temperature) and ΔSLP, that are effective on the rainfall variations in the study region. Two types of ANNs called MLP(Multi-Layered Perceptron) and ELMAN are considered in this study.

In the following section a brief introduction on IHACRES, downscaling and ANN models are given. Then the study area is introduced and the results of different models in runoff simulation and determining the water resources state are compared and discussed. Finally a summary and conclusion is given.

2.Methodology

The methodology of this paper is given in Figure 1. In this paper, two types of models named IHACRES and ANN, are used for long-lead runoff simulation and their performances are compared. For using the IHACRES model, first, the precipitation is simulated using the GCM output data, through two downscaling models called SDSM and LARS-WG. To employ ANN type models, effective large scale climatic signals on runoff variations are identified through statistical analysis and then used as model input for runoff prediction. The considered ANN models are MLP and ELMAN.

Finally the results of developed runoff prediction models (ELMAN, MLP and IHACRES) are compared. Based on the obtained results, SWSI time series are calculated in order to determine the water resources state of the study area in the future. The flow chart of methodology is shown in Figure 1.For consistency of rainfall scenario predictions using GCM data, both present as well as future predictions of GCM data should be employed for generating runoff values. Having employed the calibrated rainfall-runoff model, both present and future runoff values are simulated and then compared for future projections.

2.1. IHACRES Model

Development of mathematical models, relating the regional precipitation to the runoff, has been a major focus of surface water hydrology for many decades. There are different hydrological models used for rainfall- runoff modeling with different characteristics and limitations. TheIHACRESmodel is developed by Jakeman and Hornberger [18]. This model requires limited input data including basin size (m^2), a time series of rainfall, streamflow data for model calibration and a surrogate variable representing evaporation. In this study the monthly mean of air temperature is used as a representative of evaporation. According to Figure 2, first rainfall r_k is converted into effective rainfall u_k using a non-linear loss module. The underlying conceptualization of this module, in converting rainfall to effective rainfall, is that the basin wetness varies with recent rainfall and temperature.

$$u_k = s_k * r_k \tag{1}$$

where s_k (basin wetness index) is computed at each time step k on the basis of recent rainfall and temperature as follows:

$$s_k = C \times r_k + \left(1 + \frac{1}{\tau_w(t_k)}\right) s_{k-1} \quad s_0 = 0 \tag{2}$$

$$\tau_w(t_k) = \tau_w e^{0.062 f (R - t_k)} \quad \tau_w(t_k) > 1 \tag{3}$$

R is the reference temperature and C is determined based on the mass balance between effective rainfall and runoff in the calibration period. Two major parameters in this model are τ_w and f. Parameter τ_w (the river basin drying time constant) is the value of $\tau_w(t_k)$ at a reference temperature t_k that controls the rate in which the basin wetness index (s_k)

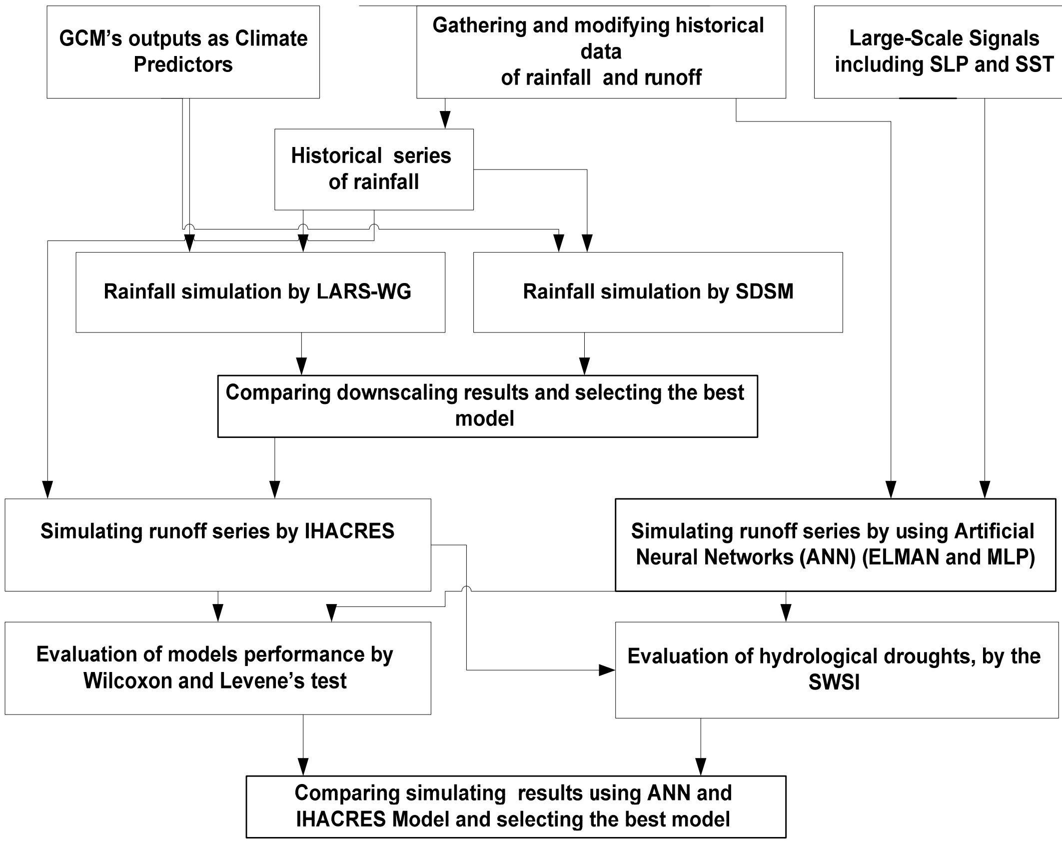

Fig. 1 The proposed methodology for runoff simulation using downscaling and ANN models

decays in the absence of rainfall. Parameter f (the temperature modulation factor) controls the sensitivity of τ_w (t_k) to temperature. In the second module a linear unit hydrograph (UH) module converts effective rainfall to streamflow x_k. The linear module allows the application of the well-known unit hydrograph theory which conceptualizes the river basin as a configuration of linear storages acting in series and/or parallel. The configuration of linear storage in the UH module which is allowed in IHACRES includes a single storage or two storage units, in series or parallel.

The optimal pair of (τ_w ,f) are identified by trial and error for a given configuration of simple UH's and a given value of the pure time delay between rainfall and runoff occurrence. Then the model automatically estimates the relevant parameters for a subsequent simulation.

Two indices of coefficient of determination, D, and percentage average relative parameter error (ARPE%) are used to determine the simulation error when calibrating IHACRES. High D and a low ARPE% are desirable. These parameters are estimated as follows[19]:

$$D = 1 - \frac{[\sigma_\xi]^2}{[\sigma_y]^2} \tag{4}$$

$$ARPE = \left[\left[\frac{\sigma_{a1}}{a_1}\right]^2 + \left[\frac{\sigma_{a2}}{a_2}\right]^2 + \left[\frac{\sigma_{bo}}{b_0}\right]^2 + \left[\frac{\sigma_{b1}}{b_1}\right]^2 \right] / 4 \tag{5}$$

where σ denotes standard deviation, and ξ and y denote model residuals and observed runoff, respectively. The parameters of Equation 5 are calculated using Equations 6 to 9, in which b and a are the unit hydrograph parameters, and s and q stand for slow and quick unit hydrographs, respectively.

$$b_0 = b_0^{(q)} + b_0^{(s)} \tag{6}$$
$$b_1 = b_0^{(q)} a_1^{(s)} + b_0^{(s)} a_1^{(q)} \tag{7}$$
$$a_1 = a_1^{(q)} + a_1^{(s)} \tag{8}$$
$$a_2 = a_1^{(q)} . a_1^{(s)} \tag{9}$$

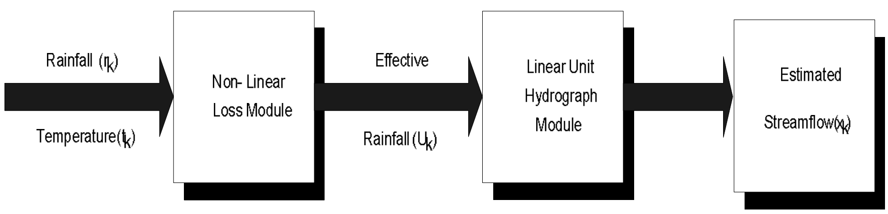

Fig. 2 The structure of the IHACRES rainfall-runoff model [18].

2-2. Downscaling Method

The input rainfall data of IHACRES model are developed using two models called SDSM and LARS-WG. The most important feature of these models is the capability of generating the ensemble data which can be used for evaluation of future risk of extreme events. These models are briefly introduced in the following subsections.

2.2.1. SDSM

In situations where low–cost, rapid assessments of localized climate change impacts are required, statistical downscaling serves as an effective tool. During downscaling using SDSM, a multiple linear regression model is developed between selected large-scale predictors and a local predictand such as temperature or precipitation. The parameters of the regression equation are estimated using the efficient dual simplex algorithm. Large-scale relevant predictors are selected using correlation analysis, partial correlation analysis and scatter plots considering physical sensitivity between selected predictors and the predictand in the region.

For precipitation downscaling, the predictors describing atmospheric circulation such as thickness (different atmospheric layers), different indices of velocity such as vorticity, zonal velocity and moisture content such as specific and relative humidity, in different altitudes, are preferred.

The utilization of SDSM includes five distinct tasks: (1) preliminary screening of potential downscaling predictors; (2) assembly and calibration of SDSM; (3) synthesis of ensembles of present weather data using observed predictor variables; (4) generation of ensembles of future weather data using GCM derived predictor variables; (5) diagnostic testing/analysis of the observed data and climate change scenarios.

2.2.2. LARS-WG

LARS-WG model is developed based on the series weather generator described in Racsko et al. [13]. It utilizes semi-empirical distributions for the lengths of wet and dry day series, daily precipitation and daily solar radiation. The semi-empirical distribution Emp= $\{a_0, a_i; h_i, i=1,...,10\}$ is a histogram with ten intervals, $[a_{i-1}, a_i)$, where $a_{i-1}<a_i$, and h_i denotes the number of events from the observed data in the ith interval. Random values from the semi-empirical distributions are chosen by first selecting one of the intervals (using the proportion of events in each interval as the selection probability) and then selecting a value within that interval from the uniform distribution. Such a distribution is flexible and can approximate a wide variety of shapes by adjusting the intervals $[a_{i-1}, a_i)$.

The intervals $[a_{i-1}, a_i)$ are chosen based on the expected properties of the weather variables. For the lengths of dry and wet series and for precipitation, the intervals $[a_{i-1}, a_i)$ size gradually increases with the increasing of i. This choice of interval structure prevents a very coarse resolution from being used for the small values.

The simulation of precipitation occurrence is modeled as alternate wet and dry series, where a wet day is defined to be a day with precipitation. The length of each series is chosen randomly from the wet or dry semi-empirical distribution for the month in which the series starts. In determining the distributions, observed series are also allocated to the month in which they start. For a wet day, the precipitation value is generated from the semi-empirical precipitation distribution for the particular month independent of the length of the wet series or the amount of precipitation on previous days. Therefore, in LARS-WG, rainfall modeling is a two step process like the SDSM model conditioned on wet and dry-days.

In LARS-WG downscaling unlike SDSM, large-scale atmospheric variables are not directly used in the model, rather, based on the relative monthly changes in mean daily precipitation amount and daily wet and dry series duration between current and future periods predicted by a GCM, local station climate variables are adjusted proportionately to represent climate change.

2.3. Artificial Neural Network

The second type of models for forecasting runoff in this study is the ANN. ANNs are commonly used for estimation of linear or nonlinear relations when ordinal mathematical relations can not be explored. These networks are trained with available data to simulate or predict future situations. ANNs have been used in different fields of water engineering as well as rainfall and runoff simulation and prediction. Different models of ANNs are classified into two main groups named static and dynamic models. Static models only consider inputs of each time step but in dynamical groups the effects of previous inputs of the model are also considered. In this study two ANN models are employed such as MLP and ELMAN as static and dynamic models, respectively. For rainfall prediction using ANN the following steps are considered:

- Determining the appropriate climate signals with strong enough relations with runoff variations in the study area. In this study, these signals are selected based on Karamouz [20].
- Training of models with different structures and determining the optimal structure for runoff simulation. The architecture of an ANN is defined based on the number of hidden layers, the transient function and the number of neurons in each layer. Each of these parameters plays an important role in ANN performance.
- Calibrating and validating the model
- Simulating the future runoff

2.4. SWSI-index

For evaluation of hydrological droughts, the SWSI is commonly used. The framework of adjusted SWSI-index developed by Garen, [21] is as follows:

$$SWSI_t = \frac{P_t - 50}{12} \tag{10}$$

where, p_1 is the cumulative probability of exceedance of runoff in month t in percent. The state of water resources in each month is determined based on the classified values of SWSI as it is given in Table 1.

Table 1 Determination of the hydrological state regarding SWSI classes

SWSI value	Hydrological state
+3.0 < SWSI < +4.2	High wetness
+2.0 < SWSI < +3.0	Moderate wetness
+1.0 < SWSI < +2.0	Low wetness
-1.0 < SWSI < +1.0	Almost normal wetness
-2.0 < SWSI < -1.0	Low drought
-3.0 < SWSI < -2.0	Moderate drought
-4.2 < SWSI < -3.0	Severe drought

2.5. Wilcoxon signed rank test

For constructing a hypothesis test for equality of means of observed and downscaled data (difference of two population means), the Wilcoxon signed rank method suggested by Sajjad Khan et al. [22] is used in this study. The detailed description of the theory of Wilcoxon signed rank test is given in Conover [23] and Neter et al. [24]. When it can be assumed that the population of differences is symmetrical as it is usually true in experimental settings, the Wilcoxn signed rank test is powerful for making inferences about the population median differences (η_D). Given the approximate normality of sum the signed ranks (T), the alternatives for construction of the decision rule are as follows:

$$H_0 \quad (\text{null hypothesis}) : \eta_D = 0$$
$$H_1 \quad : \eta_D \neq 0 \tag{11}$$

The appropriate decision rule to control the α risk in application of the test is calculated as follows:

$$\text{if } A_1 \leqq T \leqq A_2 \text{, conclude } H_0$$
$$\text{if } T < A_1 \text{ or } T > A_2 \text{, conclude } H_1 \tag{12}$$

whhere:

$$A_1 = 0 + z_{(\alpha/2)} \sqrt{\frac{n(n+1)(2n+1)}{6}}$$

$$A_2 = 0 + z_{(1-\alpha/2)} \sqrt{\frac{n(n+1)(2n+1)}{6}}$$

where $z_{(j)}$ is the (j) percentile of the standard normal distribution and n is the sample size. MATLAB 7.0 software was used to perform this test.

2.6. Modified Levene's test

Modified Levene's test suggested by Brown and Forsythe [25] is used in this study to test the equality of variances of downscaled and observed data. Levene's test is used when the data come from continuous, but not necessarily normal distributions. In this method, the distances of the observations from their sample median are calculated. The Levene test is defined as:

$$H_0 : \quad \sigma_1 = \sigma_2 = ... = \sigma_k$$
$$H_a : \quad \sigma_i \neq \sigma_j \text{ forat leastonepair}(i,j) \tag{13}$$

Given a variable Y with sample of size N divided into k subgroups, where N_i is the sample size of the ith subgroup and σ_i denotes the standard deviation of the *ith* subgroup, the Levene test statistic is defined as:

$$w = \frac{(N-k)\sum_{i=1}^{k} N_i (\bar{Z}_{i0} - \bar{Z}_{00})^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{N_i} (Z_{ij} - \bar{Z}_{i0})^2} \tag{14}$$

and

$$Z_{ij} = \left| Y_{ij} - \bar{Y}_{i0} \right| \tag{15}$$

where Y_{ij} is the value of the *j*th sample from the *i*th group, $\bar{Y}_{i0}$ is the mean of all Z_{ij}, $\bar{Z}_{00}$ is the mean of all Z_{ij} and $\bar{Z}_{i0}$ is the mean of the Z_{ij} for group *i* which are calculated as follows:

$$\bar{Z}_{00} = \frac{1}{N} \sum_{i=1}^{k} \sum_{j=1}^{N_i} Z_{ij} \tag{16}$$

$$\bar{Z}_{i0} = \frac{1}{N_i} \sum_{j=1}^{N_i} Z_{ij} \tag{17}$$

MINITAB 13.0 is used to perform Levene's test.

3. Study Area

The Kajoo watershed is located in the southeastern part of Iran. It is between 60°19 and 61°20 longitude and 25°30 and 26°48 latitude. Kajooriver is the main river of this watershed which is located in the south-eastern part of Iran close to Pakistan border (Figure 3).The area of this watershed is about 5511 km^2 and the mean annual precipitation on this watershed is about 218 millimeters. The 5 monthly precipitation from December to March is about 75% of annual precipitation. In general, the systems, which mainly affect the climate of Iran, can be categorized as Siberian high pressure center, Azure high pressure center, Mediterranean low pressure center or Mediterranean cyclones, and Sudanese low pressure center. These strong signals are supplemented but more scattered signals initiated at the Bay of Bengal, Indian ocean, Arabian Sea and Oman Sea which are partially responsible for rainfalls in the southeastern part of Iran.

There is a meteorological station, called "Ghasreghand and a hydrometric station named "Chandokan", upstream of the Zirdan dam. The situations of these stations are presented in Table 2. Zirdan reservoir is located in the middle of the Kajooriver. The initial height of the dam was considered to be 53 m and the height of the spillway was about 43m. The design discharge of the spillway is about 9634 m^3/s. The reservoir storage at the crust elevation is about 433 MCM and at the spillway elevation is about 207MCM.

The rainfall and runoff data from year 1971 to year 2004 are used in this study. Due to the closeness of the Ghasreghand station to the hydrometric station, the rainfall data of this station has been used for runoff Simulation. The GCM outputs for NCEP/NCAR reanalysis that are necessary for climate change impact studies are available at: http://www.cics.uvic.ca/scenarios.

Also in this study, during LARS-WG downscaling, 40 years (1961–2000) of observed weather data (daily precipitation, daily maximum and minimum temperature) obtained from

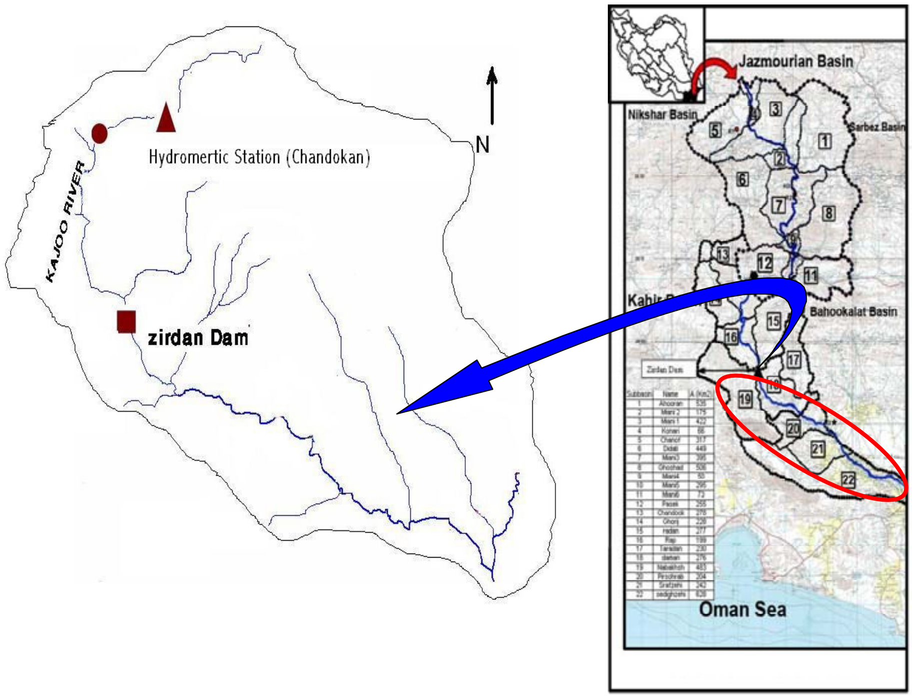

Fig. 3 The location of the Kajoo watershed on Iran map

Iranian meteorological organization are used to determine statistical parameters of the region. These statistical characteristics are used to generate synthetic data for 15 years during validation of the model. The statistical characteristics of the observed and synthetic weather data are analyzed to determine if there are any statistically significant differences using t-test, F-test and Chi-squared test. After having satisfactory test results, the parameter files derived from the observed weather data during the model calibration process were used to generate a number of ensembles of synthetic weather data for the time period of 1961–2000.

4. Results

4.1. Rainfall simulation

Karamouz et al. [26] used SDSM for daily rainfall simulation in the study area and determined relative humidity at 850 hPa height, near surface specific humidity and near surface relative humidity, as effective climate variables on rainfall variations. In this study, another downscaling model called LARS-WG is used for rainfall simulation. In this case the IHACRES model hasbeen used for transforming simulated rainfall torunoff.

To better investigate the performance of the rainfall downscaling models, error tolerance ranges are defined as percentage of simulation error, which is calculated as:

$$Error_i = \frac{|obs_i - pre_i|}{obs_i} \tag{18}$$

where obs_i and pre_i stand for observed and simulated rainfall, respectively. The percentages of simulated rainfall found in defined error tolerance ranges are calculated and summarized in Table 3 for the selected models.

As can be seen in Table 3, the performance of the SDSM model is much better than the LARS-WG. This is because of considering local signals in the SDSM model that are effective in local rainfall variations. The LARS-WG model has overestimated the amount of rainfall as shown in Figure 4. In this study the simulated rainfall by SDSM is used for rainfall-as input of rainfall-runoff models such as IHACRES.

4.2. Runoff simulation using IHACRES model

In this study, after calibration of IHACRES model, values of 1.2, 7 and 0 are estimated for parameters f, τ_w and δ, respectively. A single hydrograph has been determined as the best model that presents the system for conversion of rainfall to runoff in the study region.

The selection of the appropriate calibration period is important in achieving desirable simulation results of basin runoff using the IHACRES model. Runoff data in Chandokan station from 1982 to 1986 have been used for model

Table 2 Characteristics of Chandokanhydrometeric and Ghasre-Ghandrain gauge

Station	latitude	longitude	Height(m)
Chandokan	26-10	60-33	350
Ghasreghand	26-12	60-34	382

Table 3 Error tolerances for SDSM and LARS-WG models (Percentage of occurrence)

models	Percentage of predictions with error (%) less than		
	<10	<20	<30
LARS-WG	65	92	91
SDSM	75	100	100

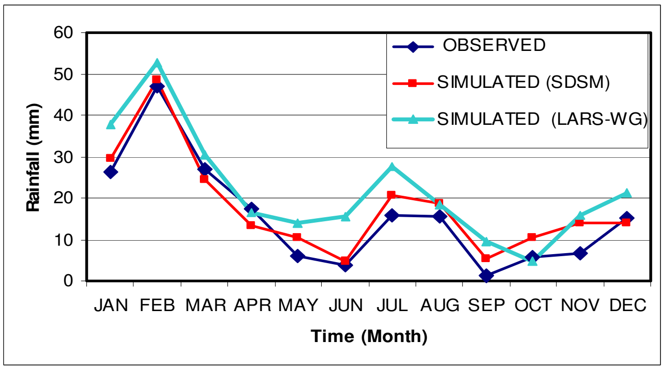

Fig. 4 Comparing downscaling results using SDSM and LARS-WG Models

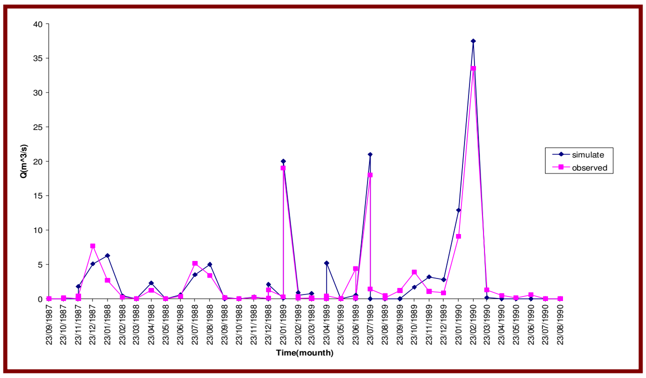

Fig. 5 Comparison of simulated and observed runoff values in the validation period

calibration and the remaining 4 years of data from 1987 to 1990 have been used for model validation. The model in calibration hasoverestimated the maximum runoff and underestimated the minimum runoff. The simulated and observed monthly runoff are compared in Figure 5 for validation period. The model behavior in the validation period is significantly different and there is usually a lag of about one month between maximum simulated and observed peak runoff. Simulation error has been estimated using MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) indices and results are shown in Table 4. These indices are quantified as follows:

$$MAE = \frac{\sum_{t=1}^{n} \left| X_p^t - X_o^t \right|}{n} \tag{19}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} \left(x_p^t - x_o^t \right)^2}{n}} \tag{20}$$

where n denotes the number of data, and X_0^t and X_p^t correspond to the observed and simulated runoff at time t, respectively. A value equal to zero corresponds to a perfect match of simulated runoff to the observed data.

Having validated the model, runoff values for three years from 1991 to 1999 has been estimated using downscaled rainfall data by SDSM (Figures 6).

4.3. Results of runoff simulation using ANN

Four effective climate signals on runoffvariations of the study region are considered for runoff simulation using ANN models [20 and 27]. Four combinations of predictors considered for ANN models developmentsare as follows:

• Comb 1: the ΔSLP between Greenland and Azors, ΔSLP between east and west of the Mediterranean Sea.

• Comb 2: the SLP of the Black sea in addition to signals considered in scenario 1

• Comb 3: considered signals in scenario 1 with a total runoff volume of last year in the period of December-April

• Comb 4: the runoff volume in the period of December-April of last year in addition to signals considered in the second scenario.

The effective climatic signals are determined based on their correlations with runoff variations in the study region. Due to high correlation of identified ΔSLP signals with runoff, in the base scenario, these signals are considered.For other scenarios, some surrogate variables, which also have a considerable correlation with runoff, are added to model inputs.

ANN models with different structures were trained considering these four scenarios as model inputs. The performances of models are compared based on RMSE and MAE indicators of error to select the best model. Results of the total 5 month runoff simulations using ANN models are presented in Figure 7. ELMAN performance in simulation of maximum events is better than MLP and in low flow periods the performance of MLP is better. According to Table 5, error indicators are a little high but, as it can be seen in Figure 7 models have been successful in the simulation of runoff variation.

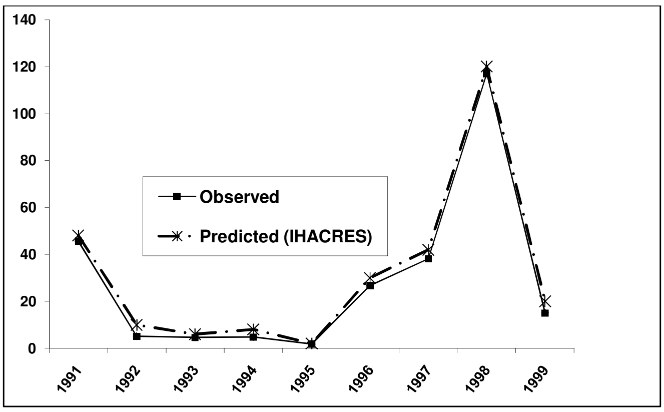

Fig. 6 Comparison of 5 monthly mean observed and predicted runoff based on IHACRES results for the years of 1991-1999

Table 4 Prediction errors in calibration and validation periods

	Calibration error (m^3/s)	Validation error (m^3/s)
MAE	1.38	4.00
RMSE	1.63	4.69

Table 5 Errors of the best trained ANN models

	MLP (m^3/s)	ELMAN (m^3/s)
RMSE	7.7	6.8
MAE	5.4	5.2

4.4. Comparison of different models results

The results of 5 monthly runoff simulation obtained using the downscaling method and the ANN model have been compared with observed values 1991 to 1999 in Figure 8. As can be seen in this figure, IHACRES results are over estimated. The estimated percentage error in dry years is more than wet days and exceeds about 95% in 1992, though the average over-estimated percentage error is 23%. The simulated values of ANN models fluctuate around observed values, and most of the time they are less than observed values. The averages of absolute percentage of errors are 23.2 and 42.8 for MLP and ELMAN models, respectively. So, that for decision making about floods, IHACRES gives more reliable results, but in drought management studies the ANN models are more confident. In some years ANN calculates simulated flow about 30% less than the observed values. This may result in implementing high risk mitigation programs with high costs that are not logical choices. The percentage of simulation with absolute errors of less than 10, 20 and 30% in considered models are presented in Table 6. This table shows that by increasing the simulation error the MLP and IHACRES model performance become more similar but when more accurate results are necessary, the IHACRES results are more accurate than MLP.The ELMAN results in all situations are less accurate than the other models. The only exceptionis in predictions with error less than 10% in comparis on with MLP, which in this case is two times better.

For evaluation of the applicability of the runoff simulations obtained by different models, SWSI series are calculated. The SWSI is used for determination of wetness situation in each year and developing the water resources operation policies. The results of Wilcoxon rank sum and Leven's tests for preservation of mean and variance in simulated data are given in Table 7. As can be seen, the results are significant in the 95% confidence level. Therefore the results are acceptable and can be used for further analysis. The SWSI results are compared in Table 8. As it can be seen, the results of the IHACRES model are more matched with the observed values.

Table 6 Percentage of predictions with absolute percent error less than 10, 20 and 30 in different models

	<10	<20	<30
MLP	0.11	0.45	0.78
ELMAN	0.22	0.33	0.56
IHACRES	0.56	0.67	0.78

4. Summary and Conclusion

Long lead runoff simulation plays an important role in water resources management and operation. It has been demonstrated that, large scale climate signals can be used for long lead runoff simulation. Many methods have been developed for utilizing climate signals for prediction of runoff in different time scales. One of the commonly used models in this field is the ANN model application. Also in recent years downscaling models have been developed to simulate the amount of rainfall in regional scales and smaller time steps, than those developed by GCM. The result of SDSM is better than LARS-WG in this study. The predicted rainfall can be used as the input of the IHACRES model for runoff simulation. In this paper these two models are applied for long lead runoff simulation in the southwestern part of Iran. In the ANN model SLP and SLP difference are used for long-lead forecasting of rainfall and in the SDSM model relative humidity at 850 hPa height, near surface specific humidity and near Surface relative humidity have been selected. These climate signals have been selected with the best R-Squared values.

Comparing the results, it can be concluded that the MLP model performance is better than the ELMAN model. In this model, MAE is 5.2 and RMSE is 5.4 and 78% of simulation errors are within 30% of the observed values. In the IHACRES model these values are 4%, 5% and 56% of simulation errors. Using the IHACRES model these values are within 10% of the observed values. IHACRES performance is better than the ANN model even though it is a more data intensive model compared to the ANN model.

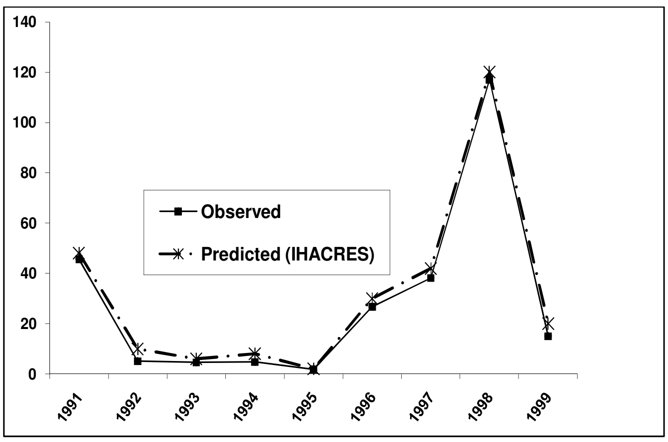

Fig. 7 Comparison of observed and simulated runoff values using two ANN models

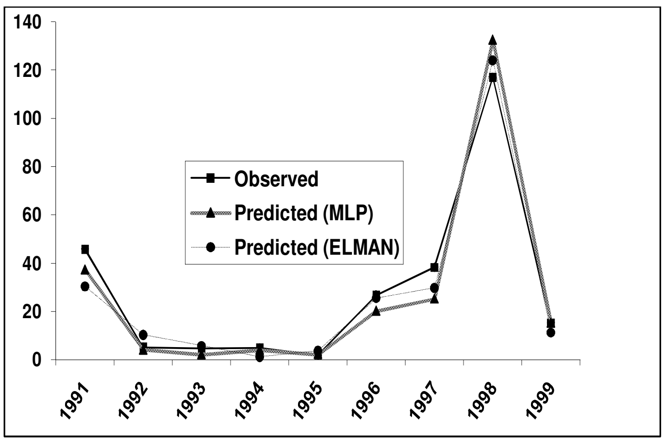

Fig. 8 Comparison of results of runoff prediction models using IHACRES and ANN Models

Table 7 The results of performing Wilcoxon rank sum tests for evaluation of simulated runoff values and SWSI index in the study area

Parameter	Model	(Variance) Leven's test		(Mean) Wilcoxon rank sum test
		p-value	T_S	p-value
SWSI	ELMAN	0.682	0.170	0.9923
	MLP	0.912	0.012	0.9768
	IHACRES	0.797	0.067	0.9304
Runoff	ELMAN	0.87	0.025	0.6048
	MLP	0.955	0.003	0.5457
	IHACRES	0.982	0.001	0.9314

Table 8 Comparison of SWSI based on the results of different models

year	ELMAN	MLP	IHACRES	Observed
1975	1.36	0.72	-0.24	-0.58
1976	0.88	0.63	-0.04	-0.15
1977	-0.02	-1.02	-1.79	-1.53
1978	1.81	2.21	2.04	2.27
1979	1.41	2.25	1.42	1.70
1980	-2.01	-2.22	-2.81	-2.34
1981	1.70	1.58	-0.46	-0.35
1982	4.10	4.10	4.12	4.10
1983	1.46	1.11	0.94	1.31
1984	-1.70	-2.24	-2.46	-2.43
1985	-3.44	-3.37	-3.86	-3.50
1986	-2.70	-1.90	-2.81	-2.80
1987	2.16	2.72	2.68	2.67
1988	1.21	1.07	-0.24	-0.02
1989	-3.80	-3.37	-2.46	-3.93
1990	1.36	1.62	1.31	1.59
1991	1.84	2.35	2.88	2.96
1992	-1.06	-2.97	-1.21	-2.00
1993	-2.44	-3.73	-2.46	-2.16
1994	-4.04	-2.99	-1.79	-2.12
1995	-3.20	-3.64	-3.86	-3.50
1996	1.41	0.89	1.89	1.99
1997	1.79	1.46	2.63	2.67
1998	3.84	3.88	3.89	3.86
1999	-0.82	0.13	0.80	0.66
Error	0.36	0.32	0.12	

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