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Statistical downscaling of climate data to estimate streamflow in a semi-arid catchment

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Abstract

Linear and non-linear statistical 'downscaling' study is done to relate large-scale climate information from a general circulation model (GCM) to local-scale river flows in west Iran. This study aims to investigate and evaluate the more promising downscaling techniques, and provides a through inter comparison study using the Karkheh catchment as an experimental site in a semi arid region for the years of 2040 to 2069. A hybrid conceptual hydrological model was used in conjunction with modeled outcomes from a General Circulation Model (GCM), HadCM3, along with two downscaling techniques, Statistical Downscaling Model (SDSM) and Artificial Neural Network (ANN), to determine how future streamflow may change in a semi arid catchment. The results show that the choice of a downscaling algorithm having a significant impact on the streamflow estimations for a semi-arid catchment, which are mainly, influenced, respectively, by atmospheric precipitation and temperature projections. According to the SDSM and ANN projections, daily temperature will increase up to +0.58° (+3.90 %) and +0.48° (+3.48 %) and daily precipitation will decrease up to −0.1mm (−2.56 %) and −0.4 mm (−2.82 %) respectively. Moreover streamflow changes corresponding to downscaled future projections presented a reduction in mean annual flow of $-3.7\,m^3\,s^{-1}$ and $-9.47\,m^3\,s^{-1}$ using SDSM and ANN outputs respectively. The results suggest a significant decrease of streamflow in both downscaling projections, particularly in winter. The discussion considers the performance of each statistical method for downscaling future flow at catchment scale as well as the relationship between atmospheric processes and flow variability and changes.

1 Introduction

There is a wide agreement in the international scientific society that climate change will modify climatic variables and hydrological extremes. Increasing greenhouse gases in the atmosphere leads to change air temperature and precipitation. Changes in air

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temperatures and precipitation have significant effects on the hydrological cycle. Such changes in climatic variables will also have significant impact on local hydrological regimes particularly in semi-arid catchments. The effects of climate change are projected to increase in the future because of rapid industry development and disregarding environmental regulations. Studies were shown that this phenomenon can effect on different systems such as; water resources, agriculture, environment, public hygiene, industry and economy as well (Samadi et al., 2009).

Emissions scenarios (SRES) were developed for climate change impacts studies on different fields. In order to assist in climate change studies, the number of SRES scenarios reduced, six markers scenarios have been elected based on the agreement opinion of the modeling groups. These are A1FI, A1T and A1B from the A1 family, and A2, B1 and B2 (Alfsen et al., 2007). In this research, A2 scenario was selected for climate change assessment on streamflow. In general A2 scenario predicted the greatest changes in air temperature and precipitation by the end of this century; therefore, the scenario and the period considered represent a "bad" case scenario.

This study relies on regression based statistical downscaling models (SDSM and ANN). Based on observed data, the SDSM define relationships between the large-scale variable data, derived either from climate model outputs or observations, and local-scale surface conditions. The large-scale variable data from GCMs or reanalysis data (the predictors) are chosen such that they are strongly related to the local scale conditions of interest (the predictands or response variable). The relationships can then be applied to estimate changes in river flow, or other local hydrological measures such as precipitation or air temperature, based on future projections from global or regional climate models. The SDSM is generally separated into three types of approach which can be combined: regression models, weather typing schemes and weather generators (Vrac and Naveau, 2007a). Multiple linear models, in the regression-based approach are the most applied in downscaling, for example the well known SDSM tool (Wilby et al., 2002). These assume a linear relationship between large-scale atmospheric predictors and the observed variable. However, several studies have shown that taking into

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consideration non-linearity between predictors and the predictand in statistical downscaling can improve the goodness-of-fit (Huth et al., 2008) including polynomial regression (Hewitson, 1994), recursive partitioning tree (Schnur and Lettenmaier, 1998), nearest neighbour (Zorita and von Storch, 1999), artificial neural networks (Harpham and Wilby, 2005; Khan et al., 2006) or generalized additive models (Vrac et al., 2007a; Salameh et al., 2009).

Regression-based statistical downscaling modeling framework, linking GCM outputs to a hydrological model, is usually constrained in space by the domain of calibration of the hydrological model. Furthermore the data requirement for setting the hydrological model parameters may be large, both for conceptual and fully distributed hydrological models (Arheimer and Wittgren, 1994; Eckhardt et al., 2005; Thompson et al., 2004; Habets et al., 2008). One possibility to increase the spatial extent of forecasting river flow at large spatial scales in response to climate change is to develop downscaling models able to simulate in streamflows directly from GCM atmospheric variables. Seeking a direct association between river flows and GCM outputs may be relevant to facilitate the generalization and extrapolation of river flow simulations over large spatial scales. moreover, the direct downscaling to streamflow from GCM variables usually do not take into account other important factors affecting the streamflow variability such as the land use and soil cover, assuming deterministically that those factors don't change with time.

Many studies presented that the global warming will influence on extreme hydrological events in various climate, and also the field of water resources is one of the highest priority fields with hydrological extremes in river catchments under future climate conditions in the world. However the potential impacts of climate change on hydrological extremes has received considerable attention from hydrologists during the last decade. Recent scientific literature on the impact of climate variability and change on river flow is voluminous both in the context of observations and projections (see e.g. Wilby et al., 1997, 2002, 2003; Dibike and Coulibaly, 2006; Semenov, 2007). Surprisingly, few studies have investigated such a link between atmospheric circulation patterns and flow in a

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purely predictive way, e.g., through downscaling applications particularly in a semi arid catchment. Examples include Cannon and Whitfield (2002) who applied an ensemble neural network downscaling approach to 21 catchments in British Columbia; Ghosh and Mujumdar (2008) who simulated the streamflow of an Indian river for the monsoon period using a relevance vector machine; Landman et al. (2001) who downscaled the seasonal streamflow at the inlets of twelve dams in South Africa from predicted monthly mean sea surface temperature variables; Phillips et al. (2003) who used atmospheric circulation models and regional climate predictors to generate mean monthly flows in two British rivers; Déry and Wood (2004) who have shown that the recent variability in Hudson Bay river was significantly clarified by the Arctic Oscillation over the last decades; Moradkhani and Meier (2010) applied statistical models to develop incorporate large-scale climate signals into seasonal streamflow forecasting scheme; Lawler et al. (2003) who explained the influence of changes in atmospheric circulation and regional climate variability on streamflows and suspended sediment changes in southern Iceland; and Ye et al. (2004) who applied combinations of climate and atmospheric variables to explain from about 31–55 % of the variance of the annual total discharges of three Siberian rivers. In this study, two direct downscaling strategies linking flows to GCM, here HadCM3, and outputs are investigated to estimate the flows measured at Gharebaghestan hydrological gauging station located in North Karkheh Catchment, Iran. Reanalysis data from the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP/NCAR; Kalnay et al., 1996) are applied as large-scale atmospheric predictors to calibrate the models and validate the approaches.

Climate appears to be generally changeable precipitation and temperature during the last half of the 20th century particularly in arid and semi-arid catchments. Regions with arid and semi-arid climates could be sensitive even to insignificant changes in climatic characteristics. Understanding the relationships among the hydrologic regimes, climate variables, and anthropogenic effects are important for the sustainable management of water resources in these regions. The goal of this study is to compare two statistical

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downscaling models, namely the Statistical Down-Scaling Model, and artificial neural network, then applied their downscaled results in a proper hydrologic model. In fact, the ultimate goal of downscaling approaches is to generate an estimate of meteorological variables corresponding to a given scenario of future climate so these research meteorological variables will be used as a basis for hydrological impact assessments. A schematic diagram of statistical downscaling tools on streamflow can find in Fig. 1. In this study, the "observed" large-scale atmospheric predictors from the National Centers for Environmental Prediction (NCEP) reanalysis data sets are used for calibration and validation of the downscaling models, and then the derived predictors of the Hadley Centre Coupled Model version 3 (HadCM3) are used in simulating daily precipitation and daily temperature for the current period (1961–1990) (Samadi et al., 2010). The objective of this study is to assess future streamflow in a semi arid catchment due to each downscaling model using global circulation model (GCM) simulated predictors instead of the observed NCEP predictors.

This analysis provides some indication of how each downscaling model will affect the generation of future streamflow based on the GCM outputs. In addition the focus of this study will address the two following questions:

1. Can the relationship between climate processes and the hydrological variability be modeled by the downscaling framework according to hydrological systems? As such, a wide set of NCEP/NCAR atmospheric variables are tested as potential predictors for flows.

2. As a synthesis of this work, is the proposed downscaling framework relevant for understanding future streamflow changes under climate change projection? As an illustration, future seasonal changes in flows are projected and discussed according to Karkheh regime (semi-arid area) over the region, using one GCM and one scenario (A2).

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2 Materials and methods

2.1 A brief description of statistical downscaling models

Downscaling methods are the most widely used in anticipated hydrologic impact studies under various scenarios; however, few studies have specifically focused on assessing future streamflow due to the different statistical downscaling methods, but future streamflow projections studies are still one of the hot topics particularly in arid and semi arid regions. In this research regression-based statistical downscaling models will capture for projection of future streamflow changes in a semi arid area. Statistical Regression-based downscaling methods use empirical relationships between local scale climatic variables (predictand (s)) and regional large scale variables (predictor(s)), two types of regression-based downscaling models, statistical downscaling model and artificial neural network, were applied in this study. The SDSM version 4.2 was used as linear method to downscale daily precipitation and temperature, it is a user friendly software package designed to implement statistical downscaling methods to produce high-resolution daily climate information from coarse resolution climate model data. The software also uses weather generator methods to produce multiple realizations (ensembles) of synthetic daily weather sequences. The SDSM model is a two step conditional resampling methodology. This multisided method downscaled area averaged precipitation using a combination of regression based methods and a stochastic weather generator. Precipitation at individual sites resample from their distributions dependent on the downscaled area average precipitation. Twenty ensembles of downscaled daily precipitation and daily temperature have been generated. Precipitation is modeled as a conditional process in which local daily precipitation is correlated with the occurrence of wet-days, which in turn correlated with regional scale atmospheric predictors. Temperatures are modeled as unconditional process in SDSM model, in which a direct link is assumed between the large scale predictors and local scale predictands. More detail regarding this model, including evaluations of its performance, can be found in Wilby et al. (1997, 2002, 2003).

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Neuro-Solutions 5 was applied to downscale climatic variables in non-linear method. In this model a non-linear regression relationship is developed between a few selected large-scale atmospheric predictors and catchments scale meteorological predictands. In developing that relationship different networks were used in which inputs were supplied and the network was trained using a variation of years and predictors for the case of neural network downscaling. First the networks trained with all predictors variables as input to the networks. Then a sensitivity analysis is done to determine the most relevant predictors, which should be selected for further retraining. Sensitivity analysis provides a measure of the relative importance among the predictors by calculating how the model output varies in response to variation of an input. The basic idea of sensitivity analysis is that the inputs to the neural network are shifted slightly and the corresponding change in the output is reported. The network output is then computed for a specified number of inputs above and below the mean. This process was repeated for each input. The neural network was then retrained with the few selected predictor variables independently for both predictants (daily precipitation and temperature) till acceptable validation performance was achieved.

Both downscaling models calibrated by using NCEP (National Centre for Environmental Prediction) reanalysis data as large-scale predictors (Semenov, 2007) and it also provided for HadCM3 simulations as well. The NCEP derived predictor data have been interpolated into the same grid as HadCM3, normally for each different GCM the NCEP derived predictor data will be slightly different, and it needs to re-analysis downscaling model in each time for a different GCM.

2.2 Ihacres rainfall-runoff model

2.2.1 Data availability

Typically the available data for the catchment is limited to daily precipitation and temperature and, in some cases, stream discharge. Thus the mathematical representation most often used is a rainfall-runoff model. Rainfall-runoff models fall into several cate-

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gories: metric, conceptual and physics-based models (Croke et al., 2000, 2001, 2004). Metric models are typically the most simple, using observed data (and streamflow) to characterize the response of a catchment. Conceptual models impose a more complex representation of the internal processes involved in determining catchment response, and can have a range of complexity depending on the structure of the model. Physics-based models involve numerical solution of the relevant equations of motion.

2.2.2 Model structure

The selection of the model to use is based on the issue(s) being investigated and the data available. As more complex questions are asked, more complex models are needed to provide the answers. The Ihacres model is a hybrid conceptual-metric model and is a lumped parameter model, using the simplicity of the metric model to reduce the parameter uncertainty inherent in hydrological models while at the same time attempting to represent more detail of the internal processes than is typical for a metric model (Kokkonen et al., 2003).

Figure 2 shows the generic structure of Ihacres model. It contains a non-linear loss module which converts into effective rainfall (that portion which eventually reaches the stream prediction point) and a linear module which transfers effective rainfall to stream discharge. Further modules can be added including one that allows recharge to be output. The inclusion of a range of non-linear loss modules within Ihacres increases its flexibility in being used to access the effects of climate and land use change. The linear module routes effective rainfall to stream through any configuration of stores in parallel and/or in series (Croke et al., 2002, 2003, 2004). The configuration of stores is identified from the time series and discharge but is typically either one store only, representing ephemeral streams, or two in parallel, allowing base flow or slow flow to be represented as well as quick flow. Only rarely does a more complex configuration than this improve the fit to discharge measurements (Jakeman and Hansberger, 1993).

Figure 2 shows the conversion of climate time series data to effective rainfall using the non-linear module, and the linear module converting effective rainfall to streamflow

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time series. The original structure of the Ihacres model used an exponentially decaying soil moisture index to convert into effective rainfall. Ye et al. (1997) adapted this model to improve the performance of the model in ephemeral catchments. This involved introducing a threshold parameter (l) and a nonlinear relationship (power law with exponent parameter p) between the soil moisture index and the fraction of that becomes effective rainfall.

The Ye et al. (1997) has been coded within Ihacres _v, reformulated to enable the mass balance parameter c (Eq. 1) to be estimated from the gain of the transfer function, and to reduce the interaction between the c and p parameters. The effective U_K in the revised model is given by:

$$U_K = [c\,(\Phi_k - l)]^p\, r_k \tag{1}$$

Where r_k is the observed, c, l and p are parameters (mass balance, soil moisture index threshold and non-linear response terms, respectively), and ϕ_k is a soil moisture index given in Eq. (2):

$$\phi_k = r_k + \left(1 - 1/\tau_k\right) \phi_{k-1} \tag{2}$$

With the drying rate τ_k given in Eq. (3):

$$\tau_k = \tau_w \exp\left(0.062 f (T_r - T_k)\right) \tag{3}$$

Where τ_w and $_{\tau_r}$ are parameters (reference drying rate, temperature modulation and reference temperature respectively). This formulation enables the gain of the transfer function to be directly related to the value of the parameter c, thus simplifying model calibration. This version of the model is more general than the version used within the Ihacres _PC model (Post and Jakeman, 1996) which can be recovered by setting parameters l to zero and p to one (with the soil moisture index) in the original model given by $S_k = c\Phi_k$ This version of the non-linear module is described in detail in Jakeman et al. (1990), Jakeman and Hornberger (1993) and Jakeman and Hornberger (1993).

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Examples of studies that have used this version of Ihacres (with minor modifications to the Eq. 3) can be found in Post and Jakeman (1996), Schreider et al. (1996) and Ye et al (1997). The success of these models is often influenced by the calibration skills of the user. Those with the necessary skills and experience can often afford only limited time to assist others in setting up simulations. Such models are often criticized for being over-parameterized (Hibbard, 1998; Jakeman and Hornberger, 1993; Jakeman et al., 1990). Where major validation of catchment models is through comparison of observed and modeled streamflow, it is known to be statistically unsound to model hydrographs with more than about five model parameters.

2.2.3 Model calibration and performance

A systematic manual calibration was chosen for setting up the hydrological model. The calibration relies primarily on the measured and estimated values of the model parameters available from the study area. This ensures that a physically meaningful set of initial parameter values is used for the calibration. The calibration parameter thresholds are defined as initial parameter value 75 %. The performance of the hydrological model at the end of each calibration trial is assessed by the following four statistical measures:

1. R^2 is showed a linear relationship between dependent variables and independent data that the range of it is between 0 till 1(0–1), so when the rate of R^2 is near to 1 it showed the stranger relationship between two group of data (Eq. 4).

$$R^2 = \left[\frac{\frac{1}{n} \sum_{m=1}^{n} \left(Q_O - \mu_p\right) \left(Q_M - \mu_o\right)}{\sigma_{QO} \times \sigma_{QM}} \right]^2 \quad (4)$$

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Q is flow (discharge), μ is the mean of data, σ is the variance, and n is the number of data, o and M indexes are showed independent and dependent data (model data) respectively.

2. Error in runoff Volume (EV %) (Eq. 5)

$$\mathrm{EV} = \frac{V_\mathrm{O} - V_\mathrm{M}}{V_O} \times 100\,[\%] \tag{5}$$

Where V_O is the observed, and V_M modeled total runoff volume.

3. Root Mean Squared Error (RMSE) (Eq. 6)

$$\mathrm{R}MSE = \sqrt{\frac{\sum_{i=1}^{n} (Q_o - Q_M)^2}{n}} \tag{6}$$

Q is flow (discharge), and n is the number of data; o and M indexes are showed independent and dependent data (model data) respectively.

4. Nash & Sutcliffe (Nash and Sutcliffe, 1970) efficiency criterion (E) (Eq. 7)

$$E = 1 - \frac{\sum_{t=1}^{N} \left(Q_{Ot} - Q_{Mt}\right)^2}{\sum_{t=1}^{N} \left(Q_{Ot} - \bar{Q}_O\right)^2}\,[-] \tag{7}$$

$\bar{Q}_O$ =The average observed river flow for the simulation period.

Each calibration trial is assessed according to the above described criteria. If the performance of the model is acceptable, the calibration process is completed, otherwise the initial calibration parameters are altered and the process repeated.

2.3 Application of the model in Karkheh catchment

Karkheh is one of the major catchment where is irrigating around five provinces in the west of Iran. Ghareso River sub-catchment is selected for this case study; it is

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located in the northwest of Karkheh catchment in the far western corner of Iran (Fig. 3). Ghareso is considered to be a climatically sensitive region, because the river originates in an area having high rainfall, but feeds arid and semi-arid regions in downstream. The area of Ghareso sub catchment is approximately 5793 km^2, the elevation changes from 1237 to 3350 and the mean elevation is 1555 m. The average land surface slope is 14 percent. Annual mean temperature of the study area is 14.6 °C, varying from 1.1 °C in February to 27.3 °C in August. The warmest time of year is in July when it is 26.95 °C on average, but could get up to 37.8 °C maximum. On the other hand, the coldest time of year is in January when it is 1.15 °C on average, but could get down to −4.2 °C minimum in this month. Annual average precipitation is about 447 mm, ranging from 215 mm to 785 mm. The annual rainfall occurs during 35 wet days for 74 mm for Kermanshah synoptic station inside of Ghareso sub-catchment.

The dominate land use is agriculture which covers around 67 % of the sub catchment (Landsat 1993). Wheat and barley are the major crops grown in this area. 5370 km^2 of the total area is drained into the outlet, where the main gauge station, Gharebaghestan, is located. The length of Ghareso River is 215 Km. Daily weather data for mean precipitation and temperature were obtained from the records of the main climate station (Kermanshah synoptic station) (Fig. 4) for the period of 1961–1990. Daily streamflow was collected from Gharebaghestan station for the period of 1971–2000 (Samadi et al., 2009). The main urban centre in the Ghareso sub catchment is the city of Kermanshah, which is designated as a growing centre in the capital of Kermanshah province.

Ghareso river mostly located in the Zagros mountain regions where the annual peak of flows generally occurring during the spring snowmelt. Conversely, the Ghareso regime characterizes highland regions, influenced by heavy winter rainfall which leading to maximum annual flows in the winters. Floods and droughts represent the main hydrological hazards in Ghareso sub catchment. Snowmelt is a major flood producing factor in this area, generating flood events most frequently in March. Intensive flood producing storms are most frequent in March and April. Periods of low flows usually

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occur during the summer, and the risk of droughts is highest in the months of June till September.

3 Results

3.1 Downscaling results

The river basin climate scenarios can be expressed as daily changes in mean rainfall depth and in mean temperature; these two variables are main factors at a river basin which input as observed data to downscaling models. Regression-statistical downscaling models present relationship between observed statistics and atmospheric circulation variables derived from NCEP/NCAR reanalysis data and it is one of the transfer GCM (here HadCM3) model to SRES scenarios, given that the same relationship holds during climate enhancement. The NCEP/NCAR reanalysis data are regridded to meet the HadCM3 grid size by simple interpolation. Then relevant atmospheric circulation variables are selected and derived at a grid center (34.21° N, 47.9° E) where the Kermanshah synoptic station is located. Statistical downscaling is much easier to apply than regional climate modeling, statistical downscaling is most appropriate for sub grid scales (small islands, point processes, etc.), complex/heterogeneous environments, extreme events, exotic predictands, transient change/ensembles and is not appropriate for data-poor regions where relationships between predictors and predictands may change.

The important step in both models is the choice of predictors which is constrained by three main factors. The predictor variables should be (1) reliably simulated by the GCM under consideration, (2) readily available from (in this case, daily) archives of GCM output and (3) strongly correlated with the surface variable(s) of interest. Candidate predictor variables should be: physically and conceptually sensible with respect to the predictand; strongly and consistently correlated with the predictand; readily available from archives of observed data and GCM output; and accurately modeled by the

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GCMs. It is also recommended that the candidate predictor suite contain variables describing atmospheric circulation, thickness, stability and moisture content. Large-scale relevant predictors are selected by using correlation analysis, partial correlation analysis and scatter plots in the SDSM and by sensitivity analysis in the ANN model as well.

The length of the data series available for all variables at Ghareso sub catchment is 30 yr. So, it was decided to establish climate scenarios for a period of 30 yr from the statistically downscaled series. The period coincident with the time of observation (1961–1990) is referred as a reference climate period. The changing factors of the mean rainfall statistics and the mean temperature in the subsequent one climate periods (2040–2069) of the 21st century relative to the reference climate period are evaluated. The statistical analysis of Kermanshah observed database showed that Six months sum rainfall is 200.5 (72 %); mean daily humidity is 24.8 %, maximum and average rainfall is 108 mm and 1.32 mm respectively. Maximum and minimum temperature in Kermanshah synoptic station is 34.2° and −18.5° respectively.

3.1.1 SDSM validation

The SDSM calculates statistical relationships which are developed using observed climatic variables and assumes that these relationships remain valid in the future. This model develops a relationship between large scale predictors and predictands (daily precipitation and daily temperature). Precipitation is modeled as a conditional process in this research whereby Kermanshah's daily precipitation is correlated with the occurrence of wet-days, which in turn is correlated with regional-scale atmospheric predictors. In this study, a wet day is defined as a day with non-zero daily precipitation of 0.1 mm or more. Temperature is modeled as an unconditional process in the SDSM, in which a direct link is assumed between the large scale predictors and local scale predictands. No transformation is applied to daily temperature data because daily temperature data is mostly normally distributed.

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Both the observed and HadCM3 derived predictor variables have been normalized with respect to their 1961-1990 means and standard deviations. Having re-trained the daily precipitation and temperature models using observed predictor – predictand relationships for the full 30 yr record (1961–1990), the models were next used to downscale equivalent regional predictor variables and 30 yr time-slices were considered: 1961–1990 (indicative of current climate forcing) and 2040–2069 (indicative of future climate forcing). For comparative purposes, changes in HadCM3 monthly mean precipitation and temperature were computed for the grid-box closest to Kermanshah station. In this research, mean sea level pressure, surface zonal velocity and 500 hPa divergences were determined to be the best predictors for precipitation and, mean sea level pressure, surface vorticity and 500 hPa geopotential heights were found to be the best predictors for temperature analysis in the SDSM model. Figure 5 indicates that the explanatory power of individual predictors can vary markedly on a month to month basis even for closely related predictands.

The monthly mean of daily precipitation and daily temperature is shown in Fig. 5. This comparison found that the average variation between daily downscaled precipitation and temperature (HadCM3, 1961–1990) and observed data are 0.097 mm and 2.19 °C respectively. Mean results show large precipitation amounts during spring, less precipitation in winter and less changeable precipitation through summer and autumn. The model shows increasing precipitation in, April, May, June, September and October and a large decrease in January, March, November and December totals. However, there is less agreement about the magnitude of expected increases in July and August. HadCM3 model under the SDSM projections for the 2040–2069 time periods presents a slight reduction in precipitation throughout the year (−0.11 mm). The average precipitation decreases by up to −0.53 mm in winter and slightly increases the rest of year. Future precipitation under HadCM3 outputs increases by up to +0.4 mm and +0.004 mm in the spring and summer respectively.

Figure 5 also shows changes in monthly mean temperatures between 1961–1990 and 2040–2069, for daily values and means daily temperature, respectively. For this

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variable, the SDSM suggests increased warming particularly in the month of January (+3.40 °C). The climate change scenario for the 2040–2069 time periods show a general increase in temperature throughout the year (+0.58 °C). The annual mean temperature increases from +1.15 °C (autumn) to +2.15 °C (winter) and decreases on average from −0.6 °C to −2.6 °C in spring and summer respectively. The SDSM method indicates that the greatest warming will occur in the period December–January/February, with much less warming during the remainder of the year. So the warm season is going to be slightly cooler and the rainy season (spring) is going to be much rainier. The greatest difference between daily precipitation and temperature with the model projection (had 40–69) occurred in December (0.94 mm) and January (4.1 °C) respectively; an important reason for this reduction is the passage of Mediterranean anticyclone crosses during cold season in this area which affects regional climate. Also, the important winds of the area consist of the western winds that transfer the relative humidity of the Atlantic Ocean and Mediterranean to the territory of this area in the winter causing rainfall. The northern wind that blows in summer is effective in modifying the climate in part of the area and reducing the heat, continuous stability of Azor near tropical zone in the summer is another reason of hot and intolerable climate in the summers. The "Saam" or "Somoum" wind blows only in the frontier zone making the climate very hot and intolerable in summers and also causing damages which both those reasons ignored in GCM modeling. Also, another important reason for reduction of precipitation is precipitation relates to local factors like topography which is disregarded in GCM simulation. This is due to the inability of the GCM model to resolve sub-grid scale atmospheric processes such as orographic enhancement of rainfall over the Zagros Mountains, and precludes a direct operational use.

In Fig. 6 the percentage of estimated variance for daily precipitation and daily temperatures are presented. Variance changes the difference between model and actual result of downscaled daily climatic variables by adding or reducing the amount of "white noise" applied to regression model estimates of the local process to better agree with observations. Use of this stochastic (random) component also allows the SDSM re-

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gression model to produce multiple ensembles of downscaled weather variables. The model (had 61–90) explains approximately +11.82 % and 14.9 % of the variance of daily temperature and daily precipitation respectively. The variance of daily precipitation was generally underestimated, most notably in January, March, April, November and December. Observed monthly daily temperature for 1961–1990 and 2040–2069 were reproduced by the downscaling model using the predictor variables except in winter (underestimated) and spring (overestimated). In both cases, the residuals of the daily temperature models were found to be normally distributed.

3.1.2 ANN validation

The structure of the network is built with candidate predictors in the Neurosolution 5 software. Initially all predictors are input to the model then large scale predictor variables were found to be most relevant predictors in the non-linear model, such as 500 hpa geopotential height, relative humidity at 500 hpa height, relative humidity at 850hpa height, divergence near surface, 850 hPa wind direction, near surface relative humidity, mean surface temperature, 500 hPa airflow strength.

Each set of selected predictor variables are then used to calibrate and validate the corresponding dynamic neural networks downscaling method. Several training experiments are conducted with different combinations of input time lags and number of neurons in the hidden layer until the optimum network is identified. This study found the Time Lagged Feed Forwarded Network (TLFN) are applied to establish the best Downscaling Artificial Neural Network (DANN) for the above variables using the 1961-1990 data series while the results of the other DANN models, namely multiple layer perception (MLP) and Radial Bias Function (RBF) networks, were not satisfactory. The atmospheric variables columns were tagged as input and the output column was tagged as desired. Similarly the rows must be tagged as well. The first 75 % of the rows were considered as training and the remaining 25 % were used as testing. The training process can take anywhere from 5 minutes to 2 h, depending on the amount of data as well as the numbers of epochs. In this research 3500 and 2000 epochs were appropriate for

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precipitation and temperature respectively. Theoretical results presents in the forms of a graph. The better the model, the more similar the graphs will look, and the closer to 1 the r-value will be (0.7 for precipitation and 0.91 for temperature in this research). Note that only one hidden layer and linear TanhAxon transfer function were found to be the best combination in this research. Sensitivity analysis was conducted and presented in a bar graph showing all the atmospheric variables and how much they affected the model over time. In fact sensitivity analysis provides a measure of the relative important variables by calculating how the model output varies in response to variation of an input. The basic idea of sensitivity analysis is that the inputs to the neural network are shifted slightly and the corresponding change in the output is reported. The neural network is then retrained with the few selected predictor variables independently for both predictants until an acceptable validation performance was achieved. The cross validation task was performed to predict future climate conditions of study area.

Taking into consideration that the predictand–predictors relationship is less complex in the case of temperature downscaling. Unlike the SDSM, precipitation is downscaled with ANN as an unconditional process by establishing a direct link between large-scale predictors and local scale predictand (precipitation). Moreover, the ANN model structure is considered deterministic restricting to simulate only one time series of downscaled daily precipitation and temperature.

In the downscaling phase, the HadCM3 model was compared to the observed precipitation and temperature at Kermanshah synoptic station for the base period of 1961–1990 and future period of 2040–2069 respectively. According to the ANN outputs (see Fig. 7), daily precipitation is quite reduced for most months except May, September and October, whereas it changes in summer (June and July). The difference between model (Had 2050) prediction and observed precipitation is 0.43 mm, also the largest difference between model and observed precipitation occurred in the months of March (1.89 mm) and December (1.55 mm), and less difference in August (0.01 mm) in the future years. ANN results for 2050 show large precipitation amounts during May until June and also for September; a slight increase for August and finally more reduction in

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the winter season in the future years. The greatest reduction in daily precipitation will happen from December until April; an important reason for this reduction is the passage of the Mediterranean anticyclone in the cold season in this area which affects on the regional climate (see SDSM projections). According to the ANN outputs, the rainy season is predicted to become shorter, which partially offsets the marked decrease in precipitation projected for the winter season. At the margins of the rainy season, small increases in monthly rainfall are projected in the summer. According to daily temperature projection by the ANN, the most difference between downscaling models and observed was happened in both December and January and the least difference in November and March. Temperature will increase in the winter and earlier spring times; it reduces in the summer and the end of spring seasons, and will be changeable in the autumn, however the ANN predicted greater difference in temperature compare to SDSM, but overall annual temperature increases up to 0.49 °C according to ANN projection. In addition temperature increasing has clearly significant affect on snow melting and further runoff generation and more precipitation will fall as rainfall rather than snow in the future.

In Fig. 8 the percentage of estimated variance for daily precipitation and daily temperatures is presented. The variance of downscaled daily climatic variables leads to an overestimation/underestimation of future projections. Use of this stochastic (random) component also allows users to find diverge of model and observed variables. The model (Had 61–90) explains approximately +11.12 % and 16.87 % of the variance of daily temperature and daily precipitation respectively. The variance of daily precipitation was generally underestimated, most particularly in January, March, April, November and December. Observed monthly daily temperature for 1961–1990 and 2040–2069 were reproduced by the downscaling model using the predictor variables and were slightly overestimated for the months of January, February, July, August, September and December. In this case, the residuals of the daily temperature models were found to be normally distributed.

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With respect to this result, climate change is undoubtedly threatening the water availability and the reduction of water resources and snow cover in the winter season and will put more pressure on the water resources that are already at their limit. It is thus important to address the climate change problem in our mission since it is greatly reducing the water availability in the west of Iran. Table 2 indicates the changes of climate variables under Hadcm3 model in the present and future years. In this table, the difference between the observed data and the Hadcm3 model was compared in 1961–1990 and 2040–2069 periods.

According to the SDSM and ANN projections daily temperature will increase up to 0.58° (3.90 %) and 0.48° (3.48 %), and also daily precipitation will decrease up to 0.11 mm (2.56 %) and 0.4 mm (2.82 %) respectively. The reduction of precipitation mainly in winter seems to change season's timing slightly in the future and it is also evident that winter arrives later than usual due to warming weather and changing climate. The greatest difference in future projections between the downscaling model and the observed is for December and January and the least difference in November and March in both the SDSM and ANN models respectively. Temperature will increase in the winter and earlier spring times; it reduces in the summer; the end of spring seasons and, will be changeable in the autumn according to both models. Increasing temperature will clearly affect on snow melt and further runoff generation.

The ANN model predicted an increase of temperature in the winter and decrease in spring (Table 1). Overall, an increase in temperature tends to actively increase the evaporation process and reduce the soil moisture generally. On the other hand winter precipitation will decrease and temperature will increase so it leads to earlier snowmelt which contributes to soil moisture saturation and consequently leads to rising flow and groundwater levels. Furthermore changes in the precipitation pattern from snow to rainfall in this area are caused.

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3.2 Calibration and verification

IHACRES hydrological model used with 30 years long sequence of climate data produced by the SDSM and ANN for the future climate scenario. The catchment was calibrated on a three years period from 1 January 1980 to 31 December 1983. Assure that the results will be sensitive to the time period selected. The calibration process is carried out using historical observed data at Gharebaghestan hydrometric station and the model was able to reproduce the observed flows properly. The mean simulated flows reproduce the mean observed flows quite well for mentioned hydrometric station. Introducing the threshold parameter resulted in a considerable improvement in the model fit, with R^2 (proportion of discharge variance explained) values reaching 0.808 for the calibration period. Table 2 summarizes the statistical performance measures defined by Eqs. (4)–(7) obtained from the data used for the calibration and verification of the hydrological model. The calibrated model was given objective function values: R^2 = 0.808, f = 1.7 and τw = 10. Overall model performance at this site, based on calculated R^2, RMSE, E and EV, was judged to be satisfactory and acceptable when function standards were compared. The Nash & Sutcliffe coefficient and error in runoff volume are rather less for both calibration and verification periods, and the coefficient of determination (R^2) is showing how well streamflows are likely to be predicted by the model. The model slightly underestimates total observed river flow volumes by 3–8 % for 1971–2000 period and in terms of RMSE and E measures, the model performs similarly with the data from the calibration and verification periods. Figure 9 depicts a plot of observed modeled flow over the modeled flow in calibration period for Ghareso River catchment and it shows that the model was capable of simulating flow well.

The catchment was then verified on a three years period from 1 January 1985 to 31 December 1988. Verification runs showed that the model was able to reproduce the observed flows in Gharebaghestan hydrometric station. Introducing the threshold parameter resulted in a considerable improvement in the model fit, with R^2 values reaching 0.664 for the verification period. Verification parameter values are shown in Table 2

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as well as simulated streamflows in Fig. 10 (verification period), Fig. 10 exhibits the model appropriately captured the flow and simulated the river flow profile in Ghareso River.

Therefore, after calibrating the hydrological model with the historical record, the next step in the investigation is to simulate streamflow in the catchment corresponding to future climate conditions by using the downscaled future precipitation and temperature data described in pervious sections as input to hydrologic model. Such a simulation helps to identify the possible trend in streamflow as well as streamflow value corresponding to climate change scenario.

3.3 Model simulation corresponding to future climate change scenarios

After calibrating the hydrological model with the historical data, the next step is simulating of flows corresponding to future climate conditions by using downscaled precipitation and temperature data in the downscaling experiment. Once again, the streamflow simulations made for the future time period with the same parameters used for observed period simulation (f = 1.7 and τw = 10) by Ihacres model.

The simulation is done with Ihacres hydrological model described in the previous section. Input to hydrological model consist of future daily precipitation and temperature data downscaled with SDSM and ANN. Then simulation results correspond to each combination of downscaling techniques and hydrological model for the Ghareso river catchment is presented in Figs. 11 and 12. The figures show the hydrologic simulations are based on the precipitation and temperature data downscaled with two downscaling models which described in previous sections. Therefore, the streamflow analysis may give different outcomes based on the particular combination of downscaling techniques and hydrological model employed for the simulation of flow in Ghareso River. In fact the multiyear flow simulation using SDSM and ANN outputs data fed to Ihacres model, showed good performance in capturing the annually of flows, although mean flows were underestimated in the simulation experiments. The performance of the model can

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assess by evaluating the model ability to reproduce the extreme hydrological measures which can associate to future flooding and drought.

The results displayed in Figs. 11 and 12 also revealed that the flow duration curve is uneven (particularly in ANN outputs) to climate change; however it is also evident that climate change has minor effect on flow regime but the effect becomes very serious as a small change in flow regime moves towards serious influence on water resources. Both downscaling outputs predicted a reduction in streamflow in Ghareso sub catchment under A2 scenario so it is leading to decrease the total river flow in the future. The results indicated that, on average, the GCM output downscaled with ANN gave relatively larger reduction in the streamflow than that downscaled with SDSM (see Figs. 11 and 12). The SDSM seems to result in a relatively smaller reduction in the streamflow than ANN. Moreover, the analysis indicates that the overall reduction in streamflow in more complexes in the earlier and end of 2050 by ANN projection. In fact, HadCM3 showed a slight downward trend for flood season/annual flows under SDSM method and a high downward trend for ANN outputs and thus the total annual flow fluctuates around the earlier and end of 2050s (mainly ANN outputs). Figure 13 is presented monthly average of future streamflow in Ghareso River catchment by both downscaling projections. According to this result models mostly underestimated except in March when ANN predicted more streamflow. Totally SDSM and ANN were predicted a reduction of 2 %–14 % and 4 %–28 % percent in streamflow by 2050s respectively. ANN absolutely predicted future streamflow twofold less than SDSM; moreover the most reduction will happen in April and less in July for both downscaling outputs in 2050s which will effect on irrigation and crop production in this time. In addition streamflow was predicted to change uneven in a minor rate in the future, which partially offsets the marked decrease in flow projected in the winter.

Figure 14 shows the changes of predicted mean flows corresponding to the future downscaled precipitation and temperature data. The prediction results present an average of mean flow reduction in the middle of 2050s by SDSM and a reduction of earlier and middle of 2050s by ANN outputs respectively. Finally this figure presented

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the ANN changes are more uneven comparing to SDSM changes and both models are somehow showing a slightly similar changes in the middle of 2050s.

3.4 Hydrological extremes under future climate scenarios

To meet the goals of the comprehensive study, the SDSM and ANN models used in this paper to replicate the present (baseline) climate and downscale an ensemble of different future climate change scenario in the north of Karkheh catchment. The hydrological model is run with a 30-yr long sequence of climatic data produced by SDSM and ANN for one future climate scenario. The SDSM and ANN outputs generate overall 3.7 $m^3 s^{-1}$ and 9.47 $m^3 s^{-1}$ reductions in the average annual daily flow respectively. The SDSM and ANN models were significantly predicted an uneven reduction in streamflow during 2040–2069, so this can be perhaps explained by the shift in the period of daily flows from all months. The most decreasing and increasing of SDSM prediction will happen in 2060 (12.6 $m^3 s^{-1}$) and 2050 (0.31 $m^3 s^{-1}$) respectively, while the most decreasing and increasing of ANN outputs will occur in 2042 (32.49 $m^3 s^{-1}$) and 2065 (0.8 $m^3 s^{-1}$) respectively. There is an even change of streamflow in the middle of 2050 (yr) for both downscaling projection. The SDSM simulation seems more reliable than ANN so this research results showed the response of Ghareso subcatchment to runoff is purely linear behaviors, subsequently future changing will happen according to a linear trend in this area, while ANN model is a nonlinear model and it is a proper model in multiple catchments where the responses of catchment to runoff will be complex where precipitation is distributed unevenly.

In this study, challenges imposed on water management, without forecasting consideration, by only projected temperature and precipitation increases are likely to be made as well as by substantial increasing in snowmelt, rain and snowfall in the spring months, when the reservoirs are filled to their full capacities in this time, so most water resources management strategies should concentrate on the earlier of spring as well as winter season in the future.

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4 Discussion

Changes in global climate will have significant impacts on local hydrological regimes, which will consequently have ramification on environmental as well as water resources and economic systems. The projected global climate change in the current century may have both beneficial and adverse environmental impact, but the larger changes in climate will cause the more adverse effect predominate. Moreover, relatively small climatic variations can create large changes in water resources, especially in arid and semi-arid regions, consequently watersheds, where water resources and water availability are already under stress in arid and semi-arid regions, are most likely to be highly vulnerable to these possible changes in climatic conditions. This research has been carried out using 30 yr of observed and downscaled data and it aimed to define future values by using of the potential skill of GCM data for hydrological applications. Regression- based statistical downscaling techniques applied in this study to predict future climatic condition in the study area.

Climate impact assessment on hydrological systems requires generation of future climate data series and simulation of these series through a hydrological model. Such an approach is usually referred as a suitable simulation experiment. To assess the potential impacts of climatic change on runoff in one of the Karkheh River's subcatchment, scenarios of changes in temperature and precipitation were applied as inputs into the Ihacres model, and overall Ihacres model predicted uneven and minor changes over future period. Indeed, the results at two downscaling models highlight that by using predicted precipitation and temperature data as direct input to the hydrological model, the simulated river flow substantially underestimates future river flow in the Ghareso sub catchment.

With respect to future trends, the SDSM and ANN have predicted an increase in annual temperature of Ghareso sub catchment by the 2050s to be in the range of 3.90 (.58 °C) to 3.48 (0.48 °C) percent while these techniques predicted a decrease in

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annual precipitation in the range of 2.56 (0.1 mm) to 2.82 (0.4 mm) percent in the same time period.

At the same time, the hydrological simulation which was based on the downscaled precipitation and temperature data showed an overall decreasing trend in the mean annual flow in the north of Karkheh catchment. In general the hydrologic simulation results show that, the data downscaled with ANN and SDSM resulted in a decrease in mean annual flow in the range of 15.4 to 38.8 percent in 2050s. In fact, Ghareso River flow changes corresponding to downscaled precipitation and temperature presented a reduction in mean annual flow of 3.7 $m^3 s^{-1}$ (SDSM outputs) and a reduction of 9.47 $m^3 s^{-1}$ (ANN outputs) in the future period totally. Increased temperature will have a clearly significant effect on snow melting and on runoff generation. According to the SDSM outputs the most reduction of precipitation will happen in the winter season and a slight increase during the rest of the year, also daily temperature will increase in the winter season and will be changeable in the rest of seasons. Furthermore winter precipitation will decrease and temperature will increase leading to earlier melt snow contributing to soil moisture saturation and dramatic increase of streamflow in the future and ground water level. Overall, an increase in temperature tends to actively increase the evaporation process and generally reduce the soil moisture.

ANN model predicted an increasing of temperature in winter and decreasing in spring. As well winter precipitation will decrease and temperature will increase so it leads to melt snow earlier which contribute to soil moisture saturation and consequently lead a rising flow and ground water level relevantly. In the end of winter, the rising temperature triggers snowmelt and typically generates a flow increase in the river catchment system, which may continue until spring. On the other hands, an increase/decrease of climatic variables may increase / decrease or shift the seasonality of climate/runoff as well, so future peak runoff may occur uneven in the end of winter or earlier of spring in Ghareso sub catchment. Significant increase in the snowmelt induced annual maximum daily flows can be expected due to longer snowmelt period stretched toward the end of winter, with more unevenly distributed snowmelt intensi-

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ties in Zagros mountain ranges. Overall, an increase in temperature tends to actively increase the evaporation process and reduce the soil moisture generally.

In this study, when we consider climate change impacts on monthly basis, the data downscaled with ANN and SDSM resulted in the highest reduction in streamflow in April and the highest increase in March of 5.4 % is typical by ANN projection which seems to be the results of earlier spring snow melting effect. However the same data downscaled with SDSM resulted in reduction of spring streamflow followed by the rest of year. Nevertheless, two downscaling methods resulted in a reduction of streamflow during the winter months which is consistent with the overall increase in winter temperature and its effect in reducing freezing. Significant reductions in streamflow are projected with winter decreases particularly likely to occur. Significant reductions in streamflow are also projected for late autumn as well as an increased late spring streamflow is signified in ANN projection. Least reduction will happen in the late summer season in the SDSM outputs and increasing of streamflow will occur in the late summer by ANN projections. At the same time a decreased summer drought propensity is indicated, especially by ANN model and it will decrease a smaller amount by SDSM projection eventually. Overall the SDSM and ANN projections predicted 20.94 $m^3 s^{-1}$ and 17.97 $m^3 s^{-1}$ of average future streamflow respectively and most rainfall will happen in the earlier of spring by both downscaling techniques in the future. The highest streamflow will occur in March for both downscaling models and the least streamflow will happen in September by SDSM and ANN models respectively.

However, overall the ANN presented the most noticeable shortcomings compared to the SDSM. The ANN model did not consider precipitation downscaling as a conditional process; rather it established a direct nonlinear relationship between large-scale predictors and local scale predictands suppressing the precipitation occurring process, which causes significant errors in downscaled daily precipitation. Moreover, the ANN model considered here is deterministic, restricted to create only one time series, while 20 ensembles can generate in SDSM model which can predict future climatic variables

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relatively more reliably. Furthermore the ANN model is so susceptible in the choice of network type and hidden layer which may generate more uncertainty by different users.

Overall a warmer climate and reduction of river flow would result a significant changes in water withdrawal demand and availability in the future of study area. It also identified that these implications of the changes may be significant for water resources planning and management as well as for farmers within the Karkheh catchment. Changes in river flow variability, is very important for water management planning and assessing future climate and its potential implication for river flows are a key challenge facing water resource planners in arid and semi-arid catchments. Among the most important projected impact of the climate change scenario

on Karkheh water resources are: declines low seasonal streamflow and higher water temperature particularly in the downstream of Karkheh where the climate mostly changes to semi arid condition and great reduction of winter rainfall as well as streamflow. Besides annual streamflow are expected to be lower in most of the time but occasional frequent flash floods are likely to occur in the late of spring and earlier of summer. However one of the challenges in hydrologic impact studies is the difficulty to draw a line between the one caused solely by climate change and the rest caused by any other activities different from climate change.

In general, climate change is projected to reduce streamflow in one of the main catchment in the west of Iran. The amount of change varies depending on the projected rainfall and projected temperature by changing evaporation rate. However the climatic impacts on hydrology at the regional scale are uncertain, and will be influence by a complex mix of temperature, precipitation, evaporation, soil moisture availability and runoff changes. Even without any change in precipitation, this temperature changes alone imply reduction in runoff rate and makes this area more vulnerable adjacent to natural hazards. In addition, climate change has unfavorable impacts on water resources in semi-arid catchment. In general climate change is projected to decrease streamflow and subsequently ground water recharge in north parts of Karkheh river

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catchment, but the effects of climate change on river flow is expected to increase the challenges of water supplies and flood management in the 21st century in this area.

5 Summery and conclusion

The main objective of this study is essentially to build and validate a downscaling framework of river flow directly from GCM outputs, to be used for future climate change impacts studies in the north of Karkheh catchment, Iran. The hydrological simulation which was based on the downscaled precipitation and temperature data showed average annual discharge may decrease significantly at hydrometric stations compared to current discharge conditions. In fact the modeled results provide a contribution to the debate about how river flow will change under climate change impacts. These results in estimates of future streamflow conditions by both of downscaling methods, another study (Samadi et al., 2012) included an uncertainty analysis which the accuracy of the two downscaling methods was tested first by applying the downscaling methods to a period of time with observed climate data and finally the best model was a more reliable statistical downscaling model for this region.

Moreover, this work adopted large-scale weather factors at only the nearest GCM data grid to develop the downscaling model, and used the A2 scenario data projected by HadCM3. Future work should consider large-scale weather factors from a region covering more grids in order to select the predictors and then to construct the downscaling model. Further selection of some regions which exhibited more precipitation amount can be adopted rather than the "less" amount by the models. Finally in order to evaluate whether GCMs indeed decrease the entire projection envelope of daily climatic variables, it is necessary to implement additional GCMs / RCMs models, scenario, and their updated projection data, could be used to investigate the possible change in future daily climate.

The presented results are also regionally limited, since physical properties of the river catchment and other concurrent catchment specific changes (e.g. topography,

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drainage density, and soil permeability), play an important role in the impact modeling. Moreover downscaling methods must find some way to account for extreme topography and the limitations of unevenly distributed. No downscaling technique is optimal for all applications, and may not even be adequate for particular applications. Considerable analysis, experience, and insight are required to select the most suitable method, or group of methods, and to deliver high-resolution climate scenarios at a specific site or for a specific region that are relevant to users and credible to researchers at the same time. Finally climate change effects on hydrology will impact on water availability and water resources in the future so results of this research will be useful for the government to develop proper control strategies in a semi arid region.

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Table 1. Model changes in daily precipitation and daily temperature between 1961–1990 and 2040–2069.

Change in daily Temperature (0C)				Change in daily Precipitation (mm/d)				Season
ANN		SDSM		ANN		SDSM		
Downscaled	HadCM3	Downscaled	HadCM3	Downscaled	HadCM3	Downscaled	HadCM3	
+3.7	+2.25	+2.87	+2.7	−1.28	−1.16	−0.53	−0.62	DJF
−0.73	+0.005	−0.26	+0.86	−0.97	−0.51	+0.04	+0.05	MAM
−0.72	−2.9	−0.39	+2.06	+0.42	+0.44	0.004	+0.004	JJA
−0.3	−1.9	+0.12	+2.12	+0.1	−0.2	+0.025	+0.14	SON
+0.49	−0.63	+0.58	+2.19	−0.43	−0.36	−0.11	−0.097	Annual

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Table 2. Calibrated and verification parameter values in Gharebaghestan hydrometric station.

R^2	EV (%)	RMSE	E	τw	f	parameter
station						
0.808	0.4	11.23	0.999	10	1.7	Calibration
0.664	3.06	20.6	0.663	10	1.7	Verification

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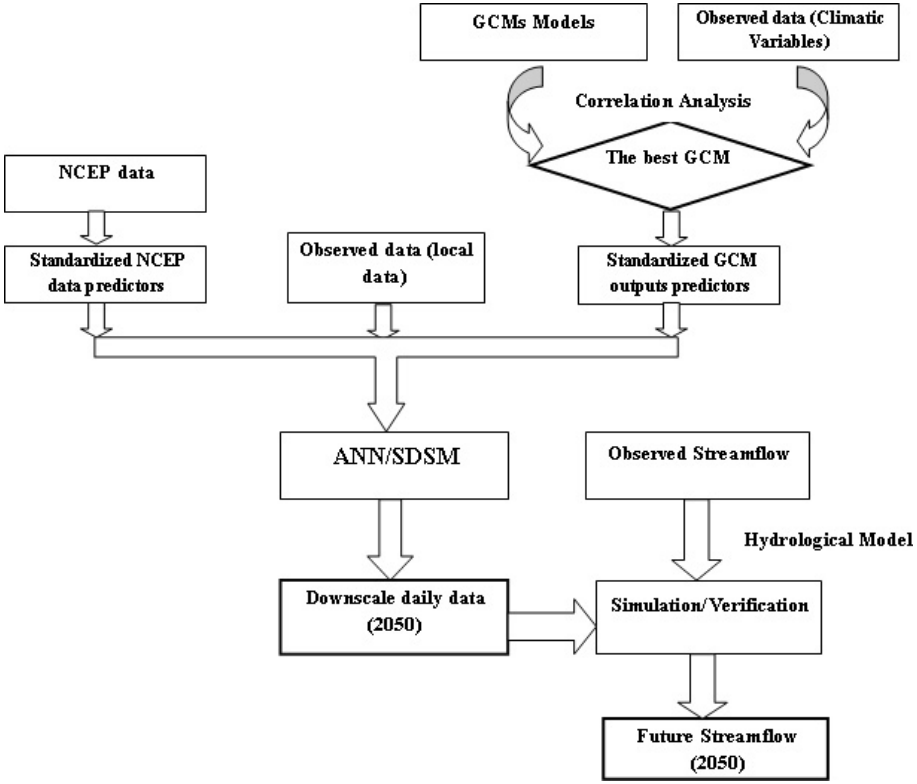

Fig. 1. Schematic illustrating of the general approach for statistical downscaling on streamflow.

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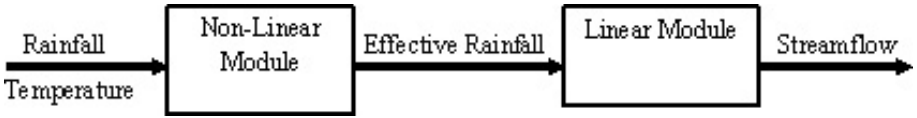

Fig. 2. Generic structure of Ihacres model (Jakeman and Hornberger, 1993 and Jakeman et al., 1990).

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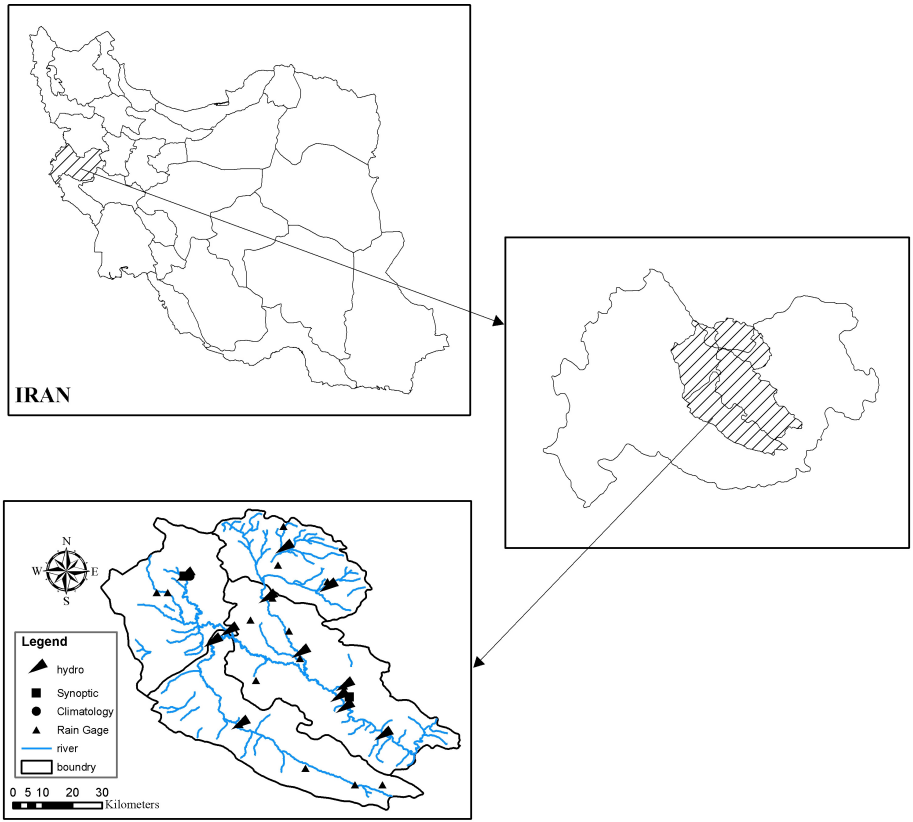

Fig. 3. Location of Ghareso sub catchment in Iran.

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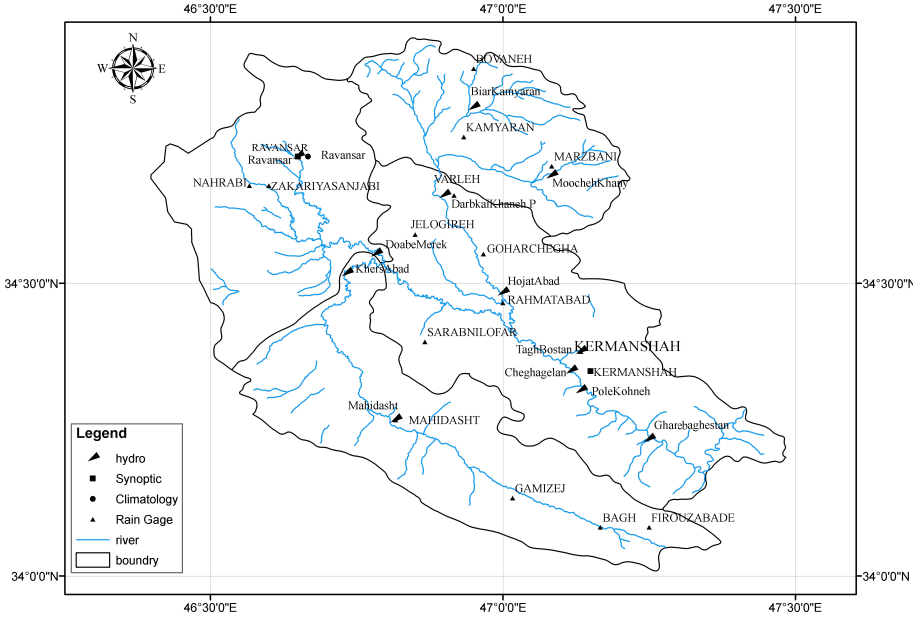

Fig. 4. Location of the Kermanashah synoptic station in the Ghareso subcatchment.

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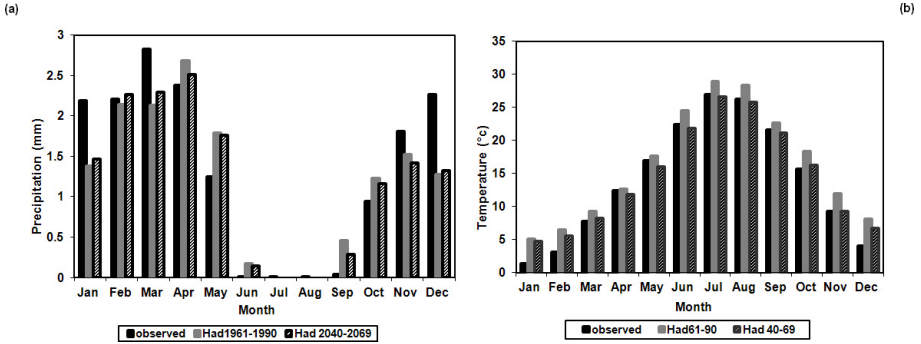

Fig. 5. Monthly mean daily precipitation **(a)** and temperature **(b)** (observed and model) using SDSM projection for the current (1961–1990) and future periods (2040–2069) in Kermanshah.

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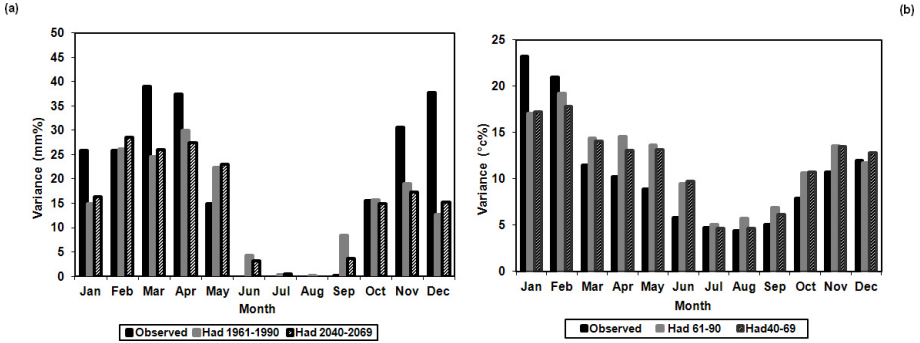

Fig. 6. Monthly variance of daily precipitation **(a)** and temperature **(b)** (observed and model) for the current (1961–1990) and future (2040–2069) periods in Kermanshah.

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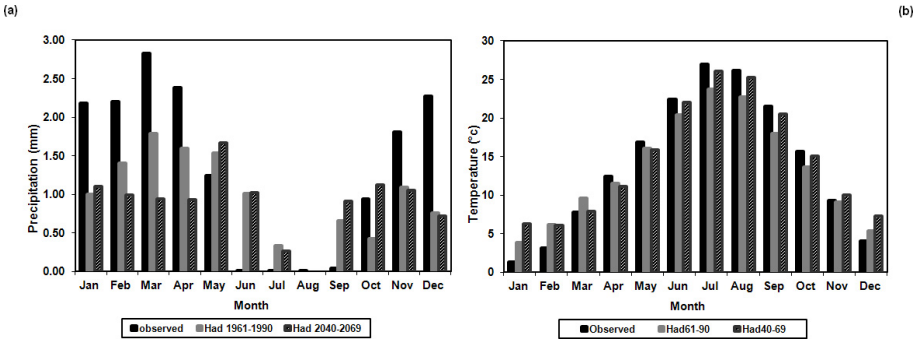

Fig. 7. Monthly mean daily precipitation **(a)** and temperature **(b)** (observed and model) using ANN projection for the current (1961–1990) and future (2040–2069) periods in Kermanshah.

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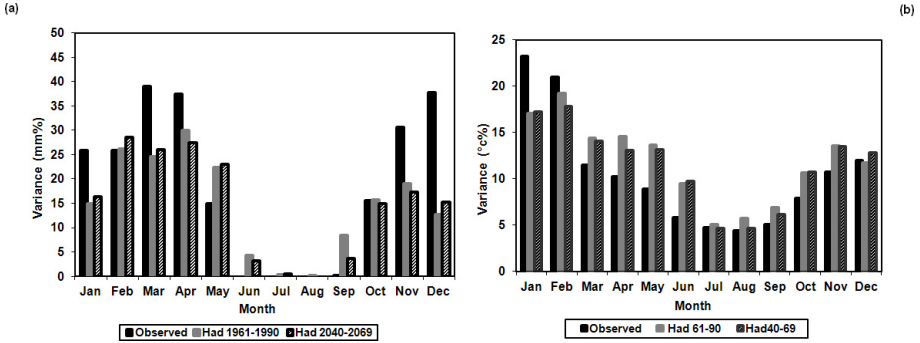

Fig. 8. Monthly variance of daily precipitation **(a)** and temperature **(b)** (observed and model) for the current (1961–1990) and future (2040–2069) periods in Kermanshah.

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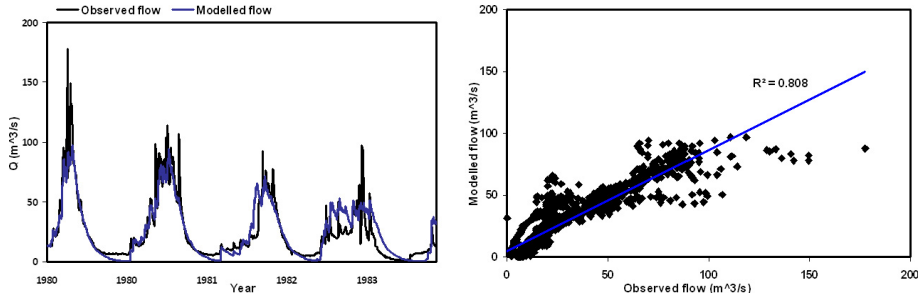

Fig. 9. Observed and modeled flows in calibration period in Ghareso river catchment.

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Statistical downscaling of climate data to estimate streamflow

S. Samadi et al.

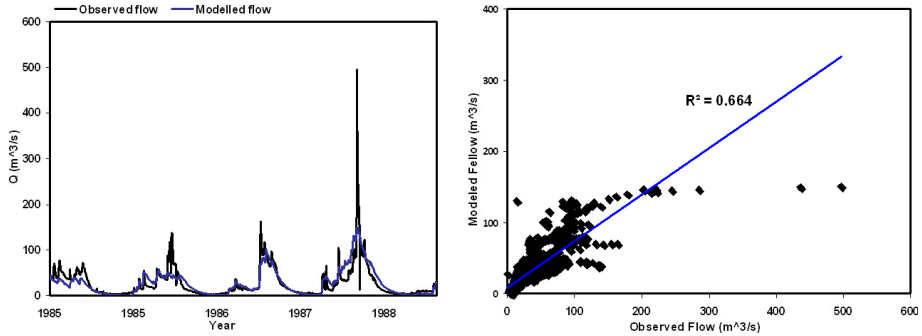

Fig. 10. Observed and modeled flows in verification period in Ghareso river catchment.

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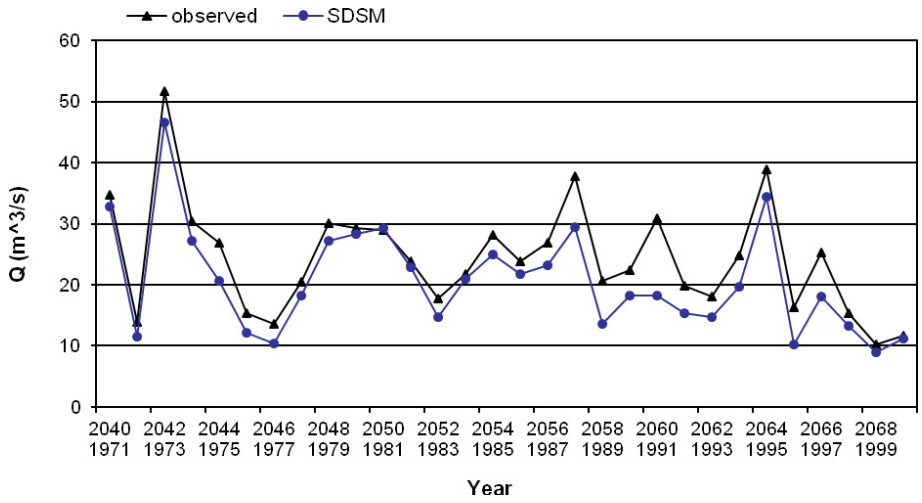

Fig. 11. Observed (1971–2000) and future (2040–2069) modeled annual streamflow using SDSM projection in Ghareso sub catchment.

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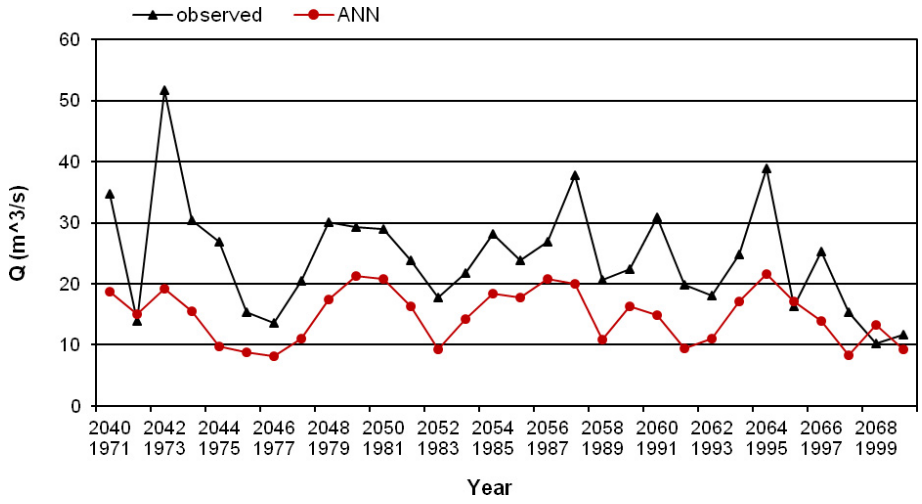

Fig. 12. Observed (1971–2000) and future (2040–2069) modeled annual streamflow using ANN projection in Ghareso sub catchment.

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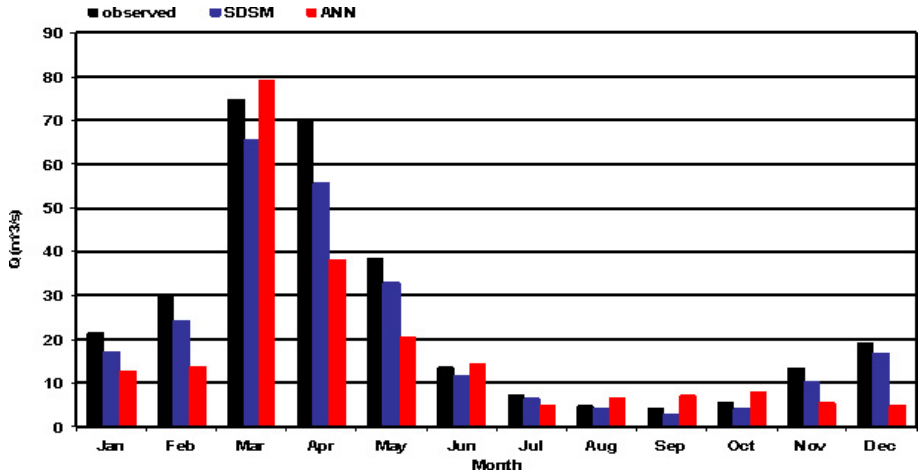

Fig. 13. Observed (1971–2000) and future (2040–2069) modeled monthly streamflow in Ghareso sub catchment.

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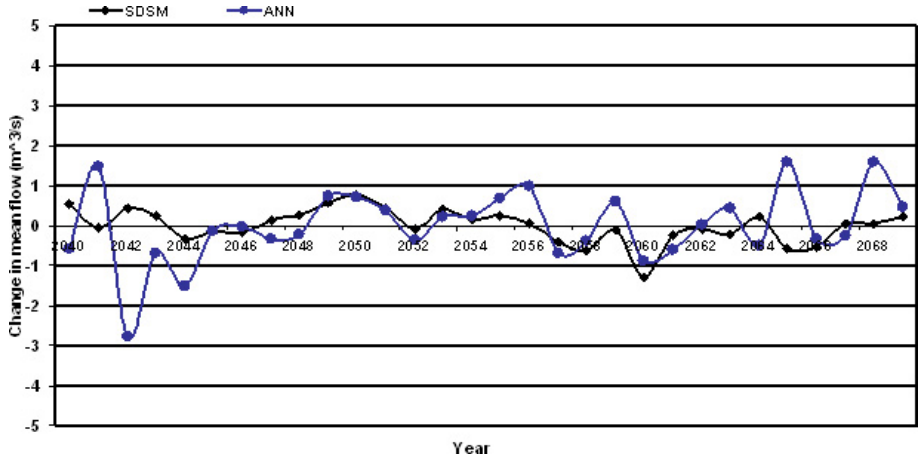

Fig. 14. Future (2040–2069) annually streamflow changes in Ghareso sub catchment.

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