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Evaluation of Climate Change Impact on Runoff: A Case Study

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Abstract

Background/Objectives: In this study we have investigating Evaluation of Climate Change Impact on runoff. **Methods/Statistical Analysis**: In this study, outputs of HADCM3 (Hadley Center Coupled Model, version 3) GCM (General Circulation Model) under A2 scenario is used to investigate the climate change impact on runoff of Gaveh Rood catchment in western Iran. The SDSM (Statistical Down Scaling Model) is employed to statistically downscale climate variables of temperature and precipitation. A runoff-rainfall Hydrological Model, named HYMOD is used for developing runoff time series under climate change impacts regarding the downscaled climate variables. **Findings:** The performance of calibrated SDSM model shows its well performance in rainfall and temperature downscaling in the study area. The downscaling results show considerable changes in temperature and precipitation in future under climate change impacts. In the period of 2020-2099, the mean temperature and precipitation is increased by 5-8.5% and 3-5%, respectively, relative to the observed period of 1989-2000. The calibration and validation results of the developed HYMOD show that it the mean runoff decreased by 7-16% (11.5%, on average) in the predicted period relative to the observed period. **Applications/Improvement**: These changes highly affect the water resources systems and special attention should be given to them in future planning of water resources.

Keywords: A2 Scenario, Climate Change, Downscaling, Gaveh Rood Basin, Rainfall-Runoff Model

1. Introduction

Climate change parameters, especially precipitation and temperature, are very important in optimal planning of water dams fed with river and runoff water flows. The fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC) says that the annual average river runoff and water availability are projected to increase by 10-40% at high latitudes and in some wet tropical areas and decrease by 10-30% over some dry regions at mid-latitudes and in the dry tropics, some of which are presently water-stressed areas[1,2]. General Circulation Models (GCMs) are commonly used for climate change impacts study[3]. The low spatial resolution (typically of the order of 50,000 km^2) of these models is capable of simulating large-scale data, which greatly limits their usefulness for local impact studies[4]. Therefore, downscaling of large-scale meteorological variables (precipitation and temperature) is necessary for investigation of climate change impact on regional hydrological characteristics[5]. Two approaches of dynamical and statistical downscaling methods are used for this purpose. Dynamical downscaling models are like GCMs but their horizontal resolutions are much finer than GCMs. In[6] used RegCM3 and RegCM4 for different climate variables downscaling. Statistical downscaling uses equations to convert global-scale output to regional-scale conditions. Regarding the less computational effort of the statistical approach, it offers the opportunity for testing scenarios for many decades, rather than the brief "time slices" of the dynamical downscaling approach. Developed Statistical Downscaling Model (SDSM) for downscaling

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precipitation and temperature data using statistical methods[7]. Compared different downscaling techniques including SDSM, radial neural network and multi-layer neural network to predict precipitation in different regions of UK. The results suggested the superiority of SDSM in precipitation simulation[3]. Explored uncertainties in downscaled precipitation and temperature data obtained from three downscaling models namely SDSM LARS-WG (Long Ashton Research Station Weather Generator) and ANN (Artificial Neural Network). The results indicated that the SDSM, LARS-WG and finally ANN have maintained different statistical characteristics of the observed data[5]. According to the previous studies on several downscaling methods, this study employed a statistical downscaling technique-based model using GCM outputs for precipitation and temperature downscaling. Considering that precipitation and temperature are the most effective meteorological variables that affect runoff, variety of models have been developed to project runoff based on precipitation and temperature data. In[8] used SWAT model to investigate the changes in the quality and quantity of runoff in the Ali Efenti Basin in the central Greece and showed flow rate reduction and increase in nitrogen density. Analyzed climate change and its impact on the flow regiment of the river catchments in the arid region of northwestern China. They used hydrometric statistics of the mean annual runoff in eight catchments and showed a declining trend in five of them[9]. Used small-scale methods and the outputs of CGM3 and HadCM3 under A2 scenarios to predict catchment runoff outflow, employing HBV and Xinan-jiang. The results suggested that regarding the precipitation difference obtained from different small-scale techniques used to feed hydrological methods, the simulation results differed[10]. HYMOD is another hydrological model with diverse applications in modeling rainfall-runoff, as well as flood warning systems. This is a non-linear conceptual model developed on the basis of Probability Distributed Model (PDM)[11,12]. This model was used in different areas[13].

This study investigates the effect of climate change on the runoff of Gaveh Rood catchment. For this purpose, rainfall-runoff of the Gaveh Rood catchment was modeled using HYMOD. After the calibration and validation of the model and ensuring its acceptable efficiency, the model was fed with precipitation and temperature data, downscaled by SDSM under SRES-A2 scenario and the effect of climate change on runoff was simulated.

2. Methods and Materials

2.1. Statistical Downscaling Methods

This study used SDSM for temperature and precipitation downscaling. It also employed large-scale meteorological signals, as well as daily observed temperature and rainfall data recorded in different rain gauges across the catchment for the period of 1989-2000. The precipitation and temperature recorded in meteorological stations are used as prediction variables in SDSM. Large-scale climatic signals are predictors were obtained from the National Center for Environmental Prediction (NCEP) and Hadley Center Coupled Model, version 3 (HadCM3). This information was obtained from the website of Canadian Climate Impacts Scenarios (CCIS), whose regional divisions have a grid-spacing of 2.50° latitude by 3.75° longitude. Among the available downscaling models, the SDSM was used for its superiority over other statistical models such as LARS-WG and ANN in regeneration of different statistical indexes of observed data with the confidence of 95%[14]. The steps required for downscaling and generating climatic scenarios in SDSM are presented in Figure 1.[7]. The meteorological signals of NCEP were used for development of the downscaling model. These signals belong to the observation period of 1971-2000. This study used HadCM3 under A2 scenario to generate meteorological variables such as precipitation and temperature in the next periods. The NCEP data were employed to ensure

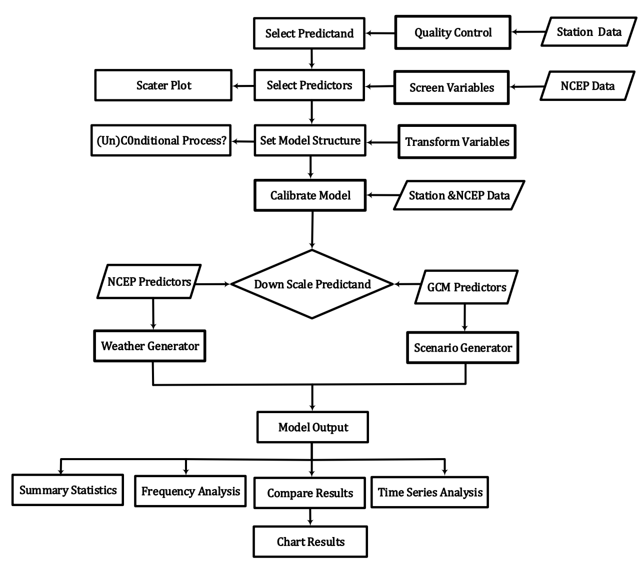

Figure 1. SDSM Version 4.2 climate scenario generation.

the stability and strength of the model in downscaling. They were also used to set the size of HadCM3 output network in the observed period.

2.1 Hydrological Models (HYMOD)

In HYMOD, a catchment is divided into an infinite number of small points with no interaction between them. Each point has a certain water storage Capacity (C) that is filled by storing rainfall [Figure 2]. Other features of these points are rainfall and potential Evapotranspiration within a specified time period. When water level in a certain point exceeds the water storage capacity of that point, the excess water becomes a surface runoff.

Water storage capacity differs due to the spatial distribution of such parameters as soil structure. Therefore, the frequency distribution function of different water storage capacities of the catchment soil is defined as follows:

$$F(C) = 1 - \left(1 - \frac{C}{C_{max}}\right)^{b_{exp}} , 0 < C < C_{max} \quad (1)$$

Where, F shows the cumulative probability of a given point in the catchment with the water storage capacity equal to C. C_{max}(in millimeter) expresses the maximum water storage capacity within the catchment's points. Finally, b_{exp} ranging from 0.1 to 2, determines the degree of spatial variability in the water storage capacity between different points of the catchment.

The HYMOD is comprised of a relatively simple rainfall excess model that is connected with two series of linear tanks including three quick-flow tanks and one slow-flow tank. This model has five parameters. Figure 3 schematically shows how HYMOD functions. The inputs of the model, namely potential Evapotranspiration, precipitation and river flow were measured to calibrate the model. The model's parameters and their scope of

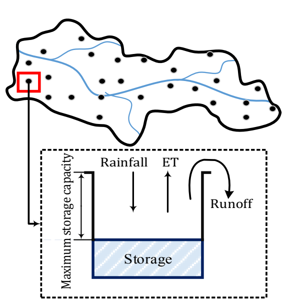

Figure 2. The schematic of the watershed and the Moore conceptual model.

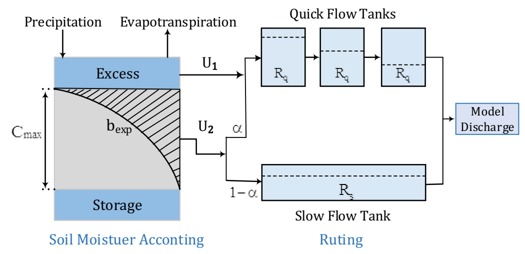

Figure 3. The schematic of HYMOD.

change are presented in Table 1. The optimal value of these parameters is obtained using genetic algorithm and regarding the given change scope in a way that the error rate between the observed and simulated runoffs was minimized by HYMOD.

The input data of HYMOD are Precipitation (P), Temperature (T), potential Evapotranspiration (ET) and Runoff (R) as presented in Equation 2. The observed runoff model is considered as the model input. Precipitation and temperature data during calibration are extracted from the information obtained from rain-gauge stations. The observed runoff data are also extracted from runoff stations. PET is also determined using Thornthwaite relation as per Equation 3[15].

Where, PET as the potential Evapotranspiration (mm), T as the mean monthly temperature (°C) and I as the annual heat index are obtained from Equation 4; a as the experimental constant is obtained from Equation 5; and as the correction factor for the number of daylight hours and days-per-month are extracted from the table according to latitude.

$$R_t = f(ET_t + P_t) \quad (2)$$

$$PET = 16L_a\left(\frac{10\bar{T}_a}{I_t}\right)^a \quad (3)$$

$$I_t = \sum_{m=1}^{12} i_m \;;\, \Big| \; i = \left(\frac{\bar{T}_a}{5}\right)^{1.514} \quad (4)$$

$$a = 6.75\times10^{-7} I_t^3 - 7.71\times10^{-5} I_t^2 + 1.792\times10^{-2} I_t + 0.4924 \quad (5)$$

2.2 Assessment Criteria

To investigate the model performance and compare the results, the indices PBIAS (Percent Bias), RSR (RMSE-Observations Standard Deviation Ratio) and NSC (Nash–Sutcliffe Efficiency) were selected.

Table 1. Prior ranges and description of the HYMOD parameters

Parameter	Unit	Description	Minimum	Maximum
C_{max}	mm	Maximum storage capacity in watershed	1	500
b_{exp}	–	Spatial variability of soil moisture distribution	0.1	2
α	–	Distribution factor between two reservoir	0	1
R_s	day^{-1}	Residence time of the slow release reservoir	0.001	0.5
R_q	day^{-1}	Residence time of the quick release reservoir	0.5	1.2

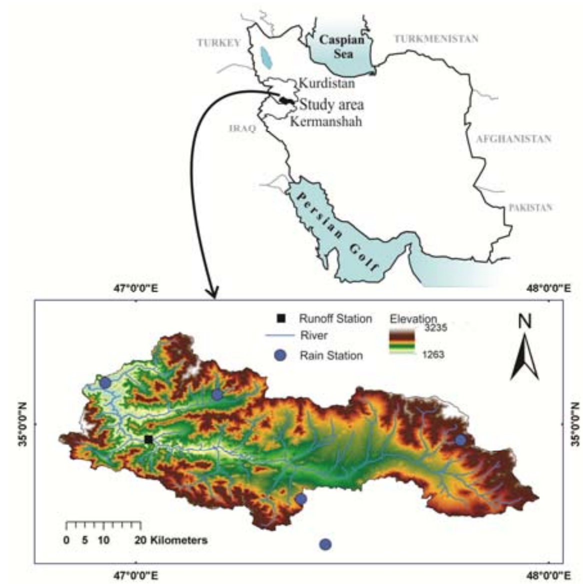

Figure 4. The location of the study area.

$$PBIAS = \frac{\sum_{i=1}^{n}\left(X_i^{obs.} - X_i^{sim.}\right)}{\sum_{i=1}^{n} X_i^{obs.}} \times 100 \quad (6)$$

$$RSR = \frac{RMSE}{STDEV_{obs.}} = \frac{\sqrt{\sum_{i=1}^{n}\left(X_i^{obs.} - X_i^{sim.}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(X_i^{obs.} - X_{mean}^{obs.}\right)^2}} \quad (7)$$

$$NSC = 1 - \frac{\sum_{i=1}^{n}\left(X_i^{obs.} - X_i^{sim.}\right)^2}{\sum_{i=1}^{n}\left(X_i^{obs.} - X_{mean}^{obs.}\right)^2} \quad (8)$$

Where $X_i^{obs.}$ the ith month is observed data, $X_i^{sim.}$ is the ith month simulated data, $X_{mean}^{obs.}$. Average of all observed data and n is the total number of month in the data series. In hydrological simulation models, when the assessment indices are applicable to the following values (NSC>0.5; RSR<0.7; and PBIAS=±25%), the results are usually satisfactory[16–18].

2.3 Case Study

This study used data from rain stations and runoff station #1 located in the catchment of Gaveh Rood river in western Iran (Figure 4). The catchment of Gaveh Rood is located in the southwestern slopes of Zagros, southern Kurdistan and northern Kermanshah. Longitude and latitude of Gaveh Rood catchment is 34°45'–35°10'N and 46°49'–47°58'E respectively.The average altitude of the catchment is 1944m above sea level. It is a semiarid region with mean annual precipitation of 457mm. The maximum monthly precipitation occurs in March and April (in total, 44% in winter). The mean temperature of the investigated region is 14.2°C. The hottest and coldest months are January and July, respectively. The location of the rain station and runoff station #1 is presented in Figure 4. The drainage basin covers an area of 2081 km^2. The 11-year observed data of the period 1989-2000 was used[19,20]. The data of the first eight years (73%) and the remaining three years (27%) were used for calibration and validation, respectively.

3. Results and Discussion

3.1 Precipitation and Temperature Predicted using SDSM Model

3.1.1 Calibration and Validation of SDSM

For development of SDSM model, the observed data of precipitation and temperature are divided into two periods, namely calibration period for development of the downscaling model and validation period for testing the model and comparing the downscaling results. The precipitation and temperature data are normalized to be used in downscaling model. Table 2 shows the assessment indices (PBIAS, RSR and NSC) considered for SDSM in the calibration and validation period for both precipitation

Table 2. The PBIAS, NSC and RSR of monthly precipitation and temperature simulations by using SDSM during the period of calibration (1989–1996) and validation (1997–2000)

Indicators	Precipitation		Temperature	
	Calibration	Validation	Calibration	Validation
PBIAS(%)	1.9	–15.9	2.05	3.05
RSR	0.49	0.37	0.18	0.11
NSC(%)	76	86	97	99

and temperature variables. These indices were measured for actual data, not for normalized data; therefore, they indicate that the performance of SDSM in predicting temperature and precipitation is very good and good, respectively.

In SDSM, to consider the correlation between precipitation and temperature (the prediction variables) with meteorological variables (the predictors), the predictions of climatic scenarios obtained from GCMs were used. In the last stage, artificial linear simulation of daily precipitation and temperature was done using GCM (HadCM3) outcomes under A2 scenarios. SDSM usually performs better in generating temperature data than precipitation data, but the rainfall data generated by this model is still satisfactory[5]. This fact is supported by the results of this study. Table 3 depicts the assessment criteria between the variables simulated by climate scenarios with precipitation and temperature data downscaled by NCEP and the values of observed precipitation and temperature.

Figures 5 and 6 compare the results obtained from the simulation of precipitation and temperature for future periods with HadCM3-A2 using SDSM and NCEP predictors. Figure 5 shows the observed precipitation versus the precipitation simulated by HadCM3-A2 as well as NCEP predictors. According to this diagram, the future precipitation decreases in the majority of months, except March, May and April when the rainfall rate increases. Figure 6 demonstrates the observed temperature versus the temperature simulated by HadCM3-A2 as well as NCEP predictors. According to this diagram, the future temperature follows an increasing trend in all months of the year. However, in some months like March, April and May, this trend is negligible.

Table 3. The PBIAS, RSR and NSC of rainfall and temperature simulations by using scenario A2, downscaling rainfall and temperature by using NCEP variables and rainfall and temperature observation during the period of 1989–2000

Options compared	Precipitation			Temperature		
	PBIAS(%)	RSR	NSC(%)	PBIAS(%)	RSR	NSC(%)
A2 scenario(HadCM3) – Observation	2	0.48	77	-2.16	0.18	97
A2 scenario(HadCM3) – Downscaling(NCEP)	3.7	0.34	89	-1.56	0.09	99

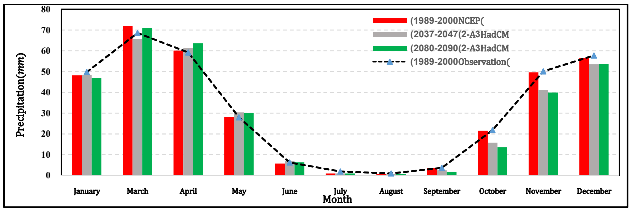

Figure 5. Observation rainfall values vs. rainfall simulations values obtained SDSM model.

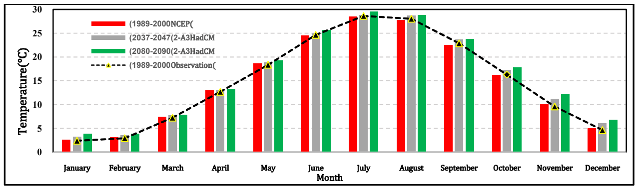

Figure 6. Observation temperature values vs. temperature simulations values obtained SDSM model.

3.2. Hydrological Models (HYMOD)

In HYMOD, 73% and 27% of data were used for calibration and validation, respectively. The results are presented in Table 5 and Figure 7 illustrates the observed values versus simulation values, showing a good match between them.

To assess HYMOD, NSC, RSR and PBIAS indices were used according to the Equations 6, 7 and 8. MSE index was used for validating the model and as the objective function for minimizing the error rate based on Equation 9 in genetic algorithm.

Table 4. Values of the HYMOD optimum parameters

C_{max}	β_{exp}	α	R_s	R_q
427	1.23	0.98	0.5	0.94

Table 5. The PBIAS, NSC and RSR of runoff simulations by using HYMOD during the period of calibration (1989–1996) and validation (1997–2000)

Indicators	Calibration	Validation
PBIAS (%)	4.99	10.1
RSR	0.49	0.55
NSC (%)	76	70

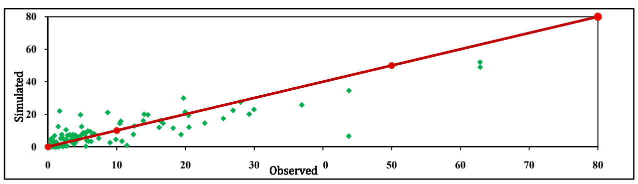

Figure 7. Observational runoff values vs. computational values obtained from HYMOD model.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(R_i^{Obs.} - R_i^{Sim.}\right)^2 \quad (9)$$

In these equations, $R_i^{Sim.}$ and $R_i^{Obs.}$ are the simulated and observed flow rates in month i and N is the total number of month in the data series.

Accordingly, the optimal values of HYMOD parameters, whose variation range is presented in Table 1 were obtained. The evaluation results are presented in Table 5. The values of PBIAS, RSR and NSC for the calibration data of this model are 4.99%, 0.49 and 76%, respectively. The values of PBIAS, RSR and NSC for the calibration data of this model are 10.1%, 0.55 and 70%, respectively. These results show relatively good, reliable performance of HYMOD in simulation of the river flow.

The HYMOD-simulated effect of climate change on runoff is presented in Figure 8. According to this figure, the runoff in the future periods follows a decreasing trend. This decline mainly occurs in the time of peak flood discharge. (Table 4)

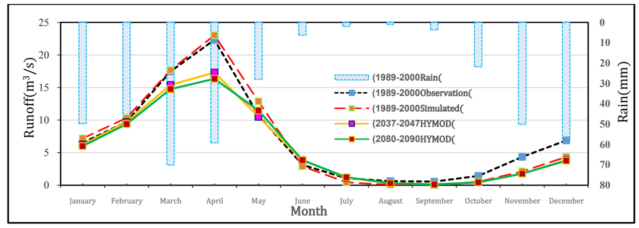

Figure 8. Observation runoff values vs. runoff simulations values for the coming period obtained HYMOD model.

4. Conclusion

This study depicted the effect of climate change on the runoff of Gaveh Rood catchment for future and in different periods. To do so, SDSM was used for downscaling precipitation and temperature series under climate change scenario. The future series of daily precipitation and temperature were generated using GCM (HadCM3) outcomes under A2 scenario. Based on the future time series of precipitation and temperature, the runoff of Gaveh Rood catchment was predicted, using HYMOD. The results are as follows:

- Decreased mean of runoff for future periods is 7-16% (11.5% on average), relative to the observation period. This decline is greater in March, May, October, November, December and April, on top, when the peak flood discharge occurs. This indicates that climate change has greater impact on extreme events. Increase in water consumption due to population growth and industrial and agricultural development on the one hand and decrease of inflow of runoff into dams on the other hand, necessitate planning for the exploitation of reservoirs to ease the damage of [water] shortage to the system.
- The predicted precipitation in the catchment shows its decreasing trend in the majority of months except March, April and May. The mean decrease in precipitation in the future periods is 3-5% (4% on average), relative to the baseline period.
- The mean temperature in the future periods shows a rising trend relative to the baseline period in the catchment. The results show an increasing trend in all months of the year. This trend is negligible in some months like March, April and May. The mean increase in temperature in the future periods is 5-8%, relative to the baseline period.

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