Uncertainty Analysis in Climate Change Projection Using Bayesian Approach

Conference Paper · May 2020

DOI: 10.1061/9780784482964.017

4 authors:


Ali Alinezhad
University of Missouri


Alireza Gohari
Isfahan University of Technology


Saeid Eslamian
Isfahan University of Technology


Ramin Baghbani
Mississippi State University

Uncertainty Analysis in Climate Change Projection Using Bayesian Approach

Ali Alinezhad[1]; Alireza Gohari[2]; Saeid Eslamian[3]; and Ramin Baghbani[4]

[1]Water Engineering Dept., College of Agriculture, Isfahan Univ. of Technology, Iran. E-mail: a.alinezhad95@ag.iut.ac.ir
[2]Water Engineering Dept., College of Agriculture, Isfahan Univ. of Technology, Iran. E-mail: ar.gohari@cc.iut.ac.ir
[3]Water Engineering Dept., College of Agriculture, Isfahan Univ. of Technology, Iran. E-mail: saeid@cc.iut.ac.ir
[4]Dept. of Agriculture and Biological Engineering, Mississippi State Univ., USA. E-mail: rb2132@msstate.edu

ABSTRACT

The evaluation of climate change impact on hydrological cycle includes uncertainty. This study aimed to evaluate the uncertainty of climate change impact on the Zayandeh-Rud Reservoir inflow during the future 2020–2049 period. The outputs of 22 GCM models have been used under the three emission scenarios including RCP2.6, RCP4.5, and RCP8.5. The Bayesian model averaging (BMA) was used as the uncertainty analysis for weighting the outputs of 22 GCM models (precipitation and temperature) based on their ability to simulate baseline 1980–2005 period. Then the time series of equivalent precipitation and temperature were introduced to the hydrological model (i.e. IHACRES) and the output of runoff was estimated under different climate change scenarios. Results showed that different GCM models have different abilities in estimating climatic variables and the application of uncertainty analysis in climate change studies is necessary. The results showed that the winter stream flow will rise by 16 to 55% under different climate change scenarios. However, a reduction of (20–50)% is expected during spring months which complicated the regional water resource management during the following warm seasons. On the annual scale, the Zayandeh-Rud Reservoir's Inflow will decrease (1–25)% under different emission scenarios which make the region more vulnerable to climate change than before. Therefore, adaptation strategies should be identified and some changes in Zayandeh-Rud Reservoir's rule curve must be applied by water resource managers in the future.

Key words: climate change, uncertainty analysis, Bayesian Model Averaging, Zayandeh-Rud, Iran.

1. INTRODUCTION

Climate change is one of the most important challenges which will intensify the global hydrologic cycle and have various effects on hydro-climatic parameters around the world. The Zayandeh-Rud River Basin, as the most strategic river basin in the Central Iran, is not exempted from this phenomenon and assessment of climate change impacts on the river flow is considered crucial regarding water resources management of the basin. According to the socio-economic development and population growth, regional water resources managers have confronted with vital problems in order to satisfy the demand of various consumer sectors of the basin in the recent decades. Therefore, the evaluation of climate change impacts on hydro-climatic variables is crucial for future decisions in the case of regional water resources. Global Climate Models (GCMs) are considered as one of the most credible tools for future climate projections which is used by many of the climate change researchers; either used as a single model (Banihabib et al., 2016; Goodarzi et al., 2015) or as a multi-model (Iizumi et al. 2009; Gohari et al. 2013; Ahmadalipour et al. 2018) for estimating meteorological parameters in different regions around the world. Whereas GCM models are considered as one of the sources of uncertainty in hydro-climatic projections, in this article the Bayesian Model Averaging (BMA) approach is utilized to analyze the embedded uncertainty in GCM's outputs and increase the level of confidence in the future climate change projections for policy makers.

The Zayandeh-Rud Reservoir is the most important structure in the basin and the effects of climate change on the Zayandeh-Rud Reservoir Inflow plays a key role in meeting the needs of different consumer sectors in the downstream regions of the reservoir. This study aims to analyze the uncertainty of hydro-climatic models in estimating the Zayandeh-Rud Reservoir Inflow by using BMA approach.

2. METHOD

The upstream sub-basin of the Zayandeh-Rud Reservoir is known as the case study of this paper which is situated between 49° 54′ to 50° 45′longitudes and 32° 18′ to 33° 12′ latitudes. The Kouhrang and Ghale-Shahrokh are selected respectively as synoptic and hydrometric stations. The monthly temperature and precipitation outputs of 22 GCM models in the fifth assessment report (AR5) of IPCC are used under the 3 emission scenarios (RCP2.6, RCP4.5 and RCP8.5) for climate change impacts assessment for the baseline (1980-2005) and future (2020-2049) periods. A general characteristics of selected stations and a brief description of the 22 GCM models are indicated in the Tables 1 and 2 respectively.

Table 1. Main characteristics of the selected stations

Station	Parameter(s)	Longitude	Latitude	Altitude (m)
Kouhrang	precipitation, temperature	50° 07′	32° 27′	2372
Ghale-Shahrokh	stream flow	50° 27′	33° 39′	2081

2.1 Generation of climate change scenarios

In order to develop climate change scenarios, the relative changes of precipitation and differences of temperature of each GCM model are calculated for each month by Equations 1 and 2.

$$\Delta P = \frac{P_{future}}{P_{base}} \tag{1}$$

$$\Delta T = T_{future} - T_{base} \tag{2}$$

where: T_{future} and T_{base} are the maximum and minimum temperature related to the future and baseline periods, respectively. In addition, the P_{future} and P_{base} are the values of rainfall for the future and historical periods, respectively.

2.2 Downscaling GCM outputs and simulating runoff

LARS-WG as one of the most well-known stochastic weather generators is here used for providing downscaled climatic variables. The observed time series of daily climatic data in historical period and generated climate change scenarios (ΔT and ΔP) were used to produce the daily time series of climatic data in the future period (Semenov and Barrow, 2002). The

IHACRES model (Jakeman and Hornberger, 1993) is then used to simulate rainfall-runoff process in the basin. In order to assess climate change impacts, the time series of downscaled precipitation and temperature are introduced to calibrated IHACRES for estimating Zayandeh-Rud Reservoir Inflow in the future.

Table 2. Description of selected GCMs under IPCC's Fifth Assessment Report (AR5)

Model	Developer	Atmospheric Resolution (Lat. × Lon.)
BCC-CSM1.1	Beijing Climate Center (China)	2.8° × 2.8°
BCC-CSM1.1(m)	Beijing Climate Center (China)	1.12° × 1.12°
BNU-ESM	College of Global Change and Earth System Science (China)	2.8° × 2.8°
CCSM4	National Center for Atmospheric Research (USA)	0.94° × 1.25°
CESM1-CAM5	Community Earth System Model Contributors (USA)	0.94° × 1.25°
CNRM-CM5	National Centre for Meteorological Research (France)	1.4° × 1.4°
CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	2.8° × 2.8°
EC-EARTH	European Community Earth-System Model (Europe)	1.1° × 1.1°
FGOALS-g2	LASG-CESS (China)	2.8° × 2.8°
FIO-ESM	First Institute of Oceanography (China)	2.8° × 2.8°
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory (USA)	2.0° × 2.5°
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory (USA)	2.0° × 2.5°
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory (USA)	2.0° × 2.5°
GISS-E2-H	National Aeronautics And Space Administration (USA)	2.0° × 2.5°
GISS-E2-R	National Aeronautics And Space Administration (USA)	2.0° × 2.5°
HadGEM2-AO	Met Office Hadley Centre (UK)	1.25° × 1.9°
HadGEM2-ES	Met Office Hadley Centre (UK)	1.25° × 1.9°
IPSL-CM5A-MR	Institut Pierre Simon Laplace (France)	1.25° × 2.5°
MIROC5	MIROC (Japan)	1.4° × 1.4°
MIROC-ESM	MIROC (Japan)	2.8 ° × 2.8°
MIROC-ESM-CHEM	MIROC (Japan)	2.8° × 2.8°
MRI-CGCM3	Meteorological Research Institute (Japan)	1.1° × 1.1°

2.3 Bayesian Model Averaging

Bayesian Model Averaging is a statistical approach to integrate forecast probability densities predicted by individual models, in order to tackle model uncertainty and generate more reliable

PDF (Raftery et al., 2005). Regarding a variable y to be forecasted based on the k models (M_1, M_2,…, M_k) and the observed data in the training period Y, the law of total probability tells us that the projected PDF is given:

$$P(y|M_1, M_2, ..., M_k, Y) = \sum_{i=1}^{k} P(M_i|Y)\, P(y|M_i, Y) \tag{3}$$

where, $P(y|M_i, Y)$ is the predicted PDF of variable y given model i, which indicates the posterior distribution of variable y given by the model M_i. This posterior probability of each model being correct to estimate the observed data (Y) during the training period ($P(M_i|Y)$) which reflects the performance of model i. Before application of BMA, a linear regression is utilized as the bias-correction method and the original model projections in the time t (M_i^t) are replaced by the bias-corrected forecast (f_i^t) (Raftery et al., 2005); i.e. ,

$$f_i^t = a_i + b_i M_i^t \tag{4}$$

where, a_i and b_i are the coefficients of linear regression model and f_i^t is the bias-corrected forecast. In the next step, the Expectation–Maximization (EM) algorithm has been used in order to optimize the weights of posterior distribution until the gap between the observations and model's forecasts converges to zero. The flowchart of EM algorithm is in Figure 1.

1st iteration

$$W_{i,Iter} = \frac{1}{k}, \qquad \sigma_{i,Iter}^2 = \frac{1}{k} \sum_{t=1}^{T} \frac{\sum_{i=1}^{k} (y^t - f_i^t)^2}{T}$$

Next iterations

$$W_{i,Iter} = \frac{1}{T} \sum_{t=1}^{T} z_{i,Iter}^t,$$

$$\sigma_{i,Iter}^2 = \frac{\sum_{t=1}^{T} z_{i,Iter}^t \cdot (y^t - f_i^t)^2}{\sum_{t=1}^{T} z_{i,Iter}^t},$$

$$z_{i,Iter}^t = \frac{W_{i,Iter-1} \cdot g(y^t | f_i^t, \sigma_{i,Iter-1}^2)}{\sum_{i=1}^{k} W_{i,Iter-1} \cdot g(y^t | f_i^t, \sigma_{i,Iter-1}^2)},$$

$$l(\theta_{Iter}) = \log(\sum_{i=1}^{k} W_{i,Iter} \cdot \sum_{t=1}^{T} g(y^t | f_i^t, \sigma_{i,Iter}^2))$$

Figure 1. The flowchart of EM algorithm

where, W_i and σ_i^2 are the weight and variance of model i respectively; T is the number of observations in the training period; and z is the latent variable.

3. RESULTS

3. 1. Uncertainty Analysis of GCMs in hydro-climatic projection

The Root Mean Square Error (RMSE) is here applied to compare the abilities of different global climate models (GCMs) and the BMA method to generate the observed hydro-climatic variables' time series in the historical 1980-2005 period (Figures 2-4). According to Figure 2, most of the GCMs showed considerable errors in projection of the observed precipitation in winter and spring months. But, the BCC-CSM1.1(m), FGOALS-g2, GFDL-CM3 and MIROC5 had relatively better abilities to estimate rainfall values in cold seasons. Regarding temperature, the majority of the GCMs showed high RMSE values during the fall and winter seasons (Figure 3). However, most of them showed better performance in warmer seasons including spring and summer months. GFDL-ESM2G, HadGEM2-AO, HadGEM2-ES and CESM1(CAM5) had better performance compared to other models in temperature prediction during the fall and winter months.

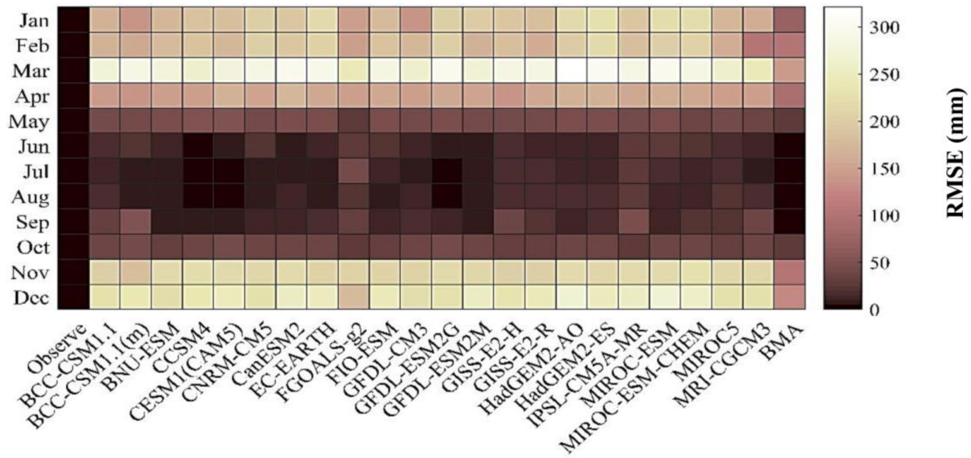

Figure 2. RMSE values of GCMs' outputs and BMA approach in simulating the observed precipitation during baseline period

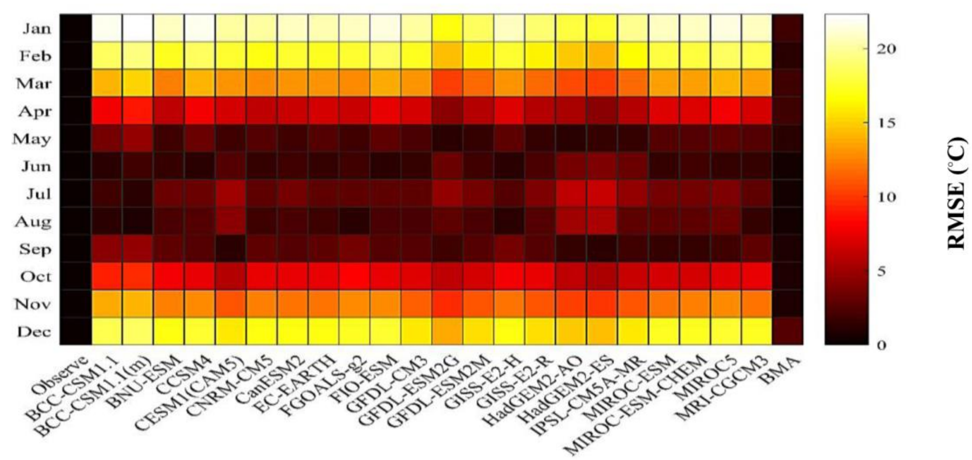

Figure 3. RMSE values of GCMs' outputs and BMA approach in simulating the observed temperature during baseline period

According to the Figures 2 and 3, some GCM models showed better abilities to estimate some climatic variables than the other ones. However, the application of BMA approach on the meteorological variables leads to better estimation of the observed values in the baseline period. Figure 4 shows the abilities of GCMs to generate the observed stream flow values during the baseline period. GCM models had minimum errors in estimating the observed runoff within the fall and winter seasons. However, most of the models revealed maximum RMSE in warm seasons especially of April and March. The FGOALS-g2, GFDL-CM3, GISS-E2-R and MRI-CGCM3 models showed the higher performance in discharge prediction. The results show that the GCMs should be considered as one of the most important sources of uncertainty in climate change studies. The application of BMA can significantly reduce the errors in the historical period. Hence, it can be concluded that application of single GCM cannot lead to a reliable prediction of hydro-climatic projection. The results showed that application of BMA before preparing climatic data for hydrological model can significantly produce better simulated runoff.

The performance of BMA approach in proving the reliable hydro-climatic estimations can be acceptable for different months. The ability of BMA in capturing the climate change impacts uncertainties on climatic variables as well as its acceptable performance in hydrological forecasts make it more appropriate for climate change studies.

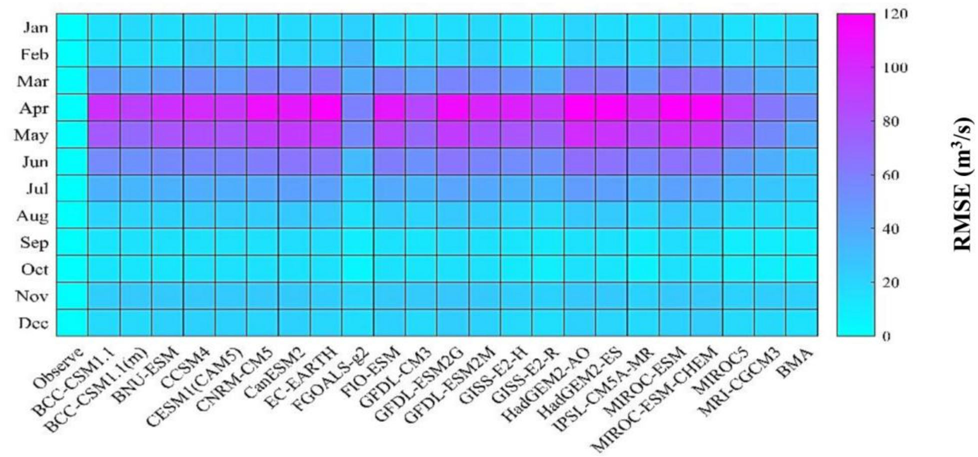

Figure 4. RMSE values of GCMs' outputs and BMA approach in simulating the observed runoff during baseline period

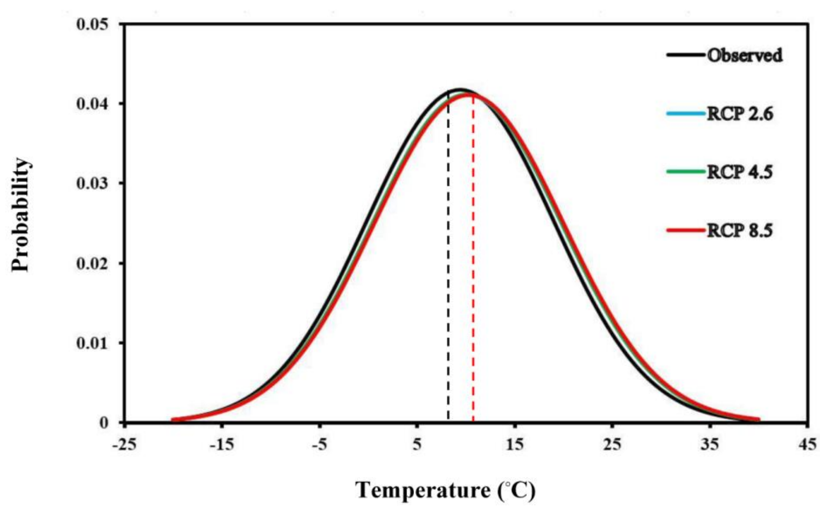

Figure 5. The PDF of annual temperature in the historical and future periods

3.2. Climate change impacts on hydro-climatic variables

The PDF of annual temperature and precipitation during the baseline and future (after application of BMA) periods are indicated in Figures 5 and 6. The average of annual temperature showed 0.5 to 1 ^{o}C increase under different climate change scenarios for the future (Figure 5). This increase in temperature can intensify the process of melting snows in the basin. Furthermore, the projected annual rainfall showed a reduction of 13 to 18 percent which will negatively alter the stream flow in the future. An increase in the average temperature coupled with a decrease in rainfall will intensify the current water shortage in the basin.

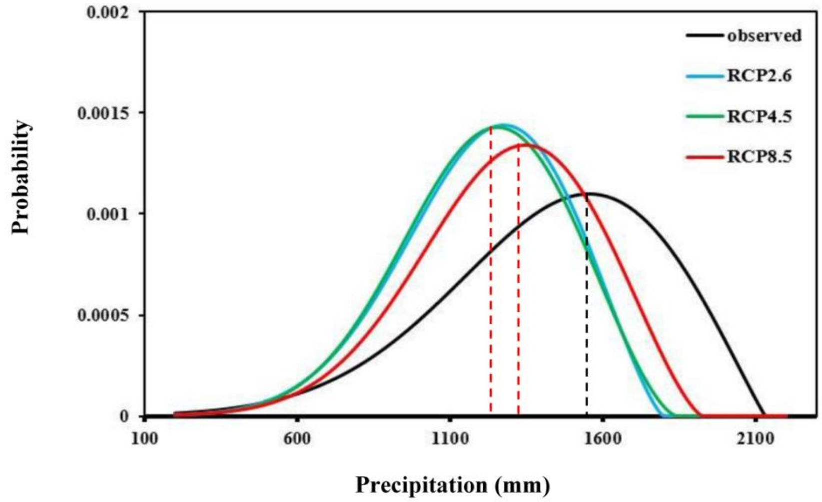

Figure 6. The PDF of annual precipitation in the historical and future periods

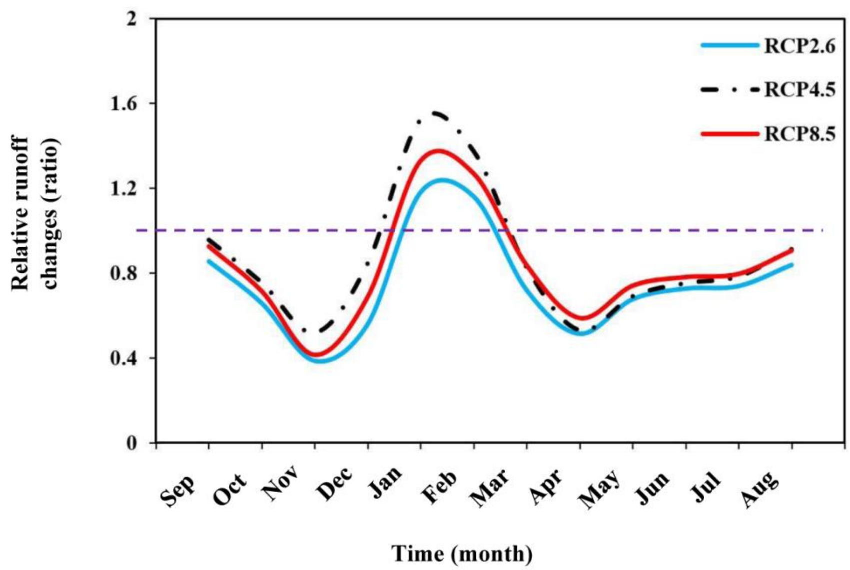

Figure 7. Expected changes of runoff under different climate change scenarios after application of BMA in the futures. The horizontal dash lines shows no changes.

Figure 7 shows the relative changes in stream flow under climate change scenarios for different months of the year. The winter stream flow rise by 16 to 55 % under different climate change scenarios. However, a reduction of (20-50) % is expected during the spring months which negatively affects the availability of water resources during the following warm seasons. The maximum decrease (62%) in stream flow is projected for November under RCP2.6. However, the stream flow of January will increase by 55% under RCP4.5.

4. CONCLUSIONS

In this study, the outputs of 22 GCMs are used under three emission scenarios to investigate the climate change impacts on the Zayandeh-Rud Reservoir Inflow for the future 2020-2049 period. To increase the reliability of hydro-climatic projections, the Bayesian Model Averaging was utilized for climate change impact assessment. The results showed that the application of BMA approach on meteorological variables, including temperature and precipitation, leads to the better estimation of the observed values for all months in the baseline period. The results obtained from the Probability Density Function of precipitation revealed a reduction of (13-18) % in probabilistic peak of annual precipitation leading to some negative consequences in the availability of water resources in the study area. At annual scale, the temperature will increase (0.5-1) °C under different climate change scenarios. Furthermore, the Zayandeh-Rud Reservoir's Inflow will decrease (1-25) % at annual scale under different climate change scenarios. These results comply with the findings of Gohari et al., 2014. However, a reduction of (20-50) % in spring runoff will push a significant pressure on water resources managers in order to satisfy the demands of various consumer sectors for the following warm seasons. The expected decreasing trend in runoff as well as the growing water demand, make the Zayandeh-Rud River Basin more vulnerable to climate change than before. Therefore, the adaptation strategies like modifying the Zayandeh-Rud Reservoir's rule curve should be implemented to moderate the plausible negative impacts of climate change on water resources in the future.

REFERENCES

Ahmadalipour, A., Moradkhani, H., Rana, A., 2018. Accounting for downscaling and model uncertainty in fine-resolution seasonal climate projections over the Columbia River Basin. Clim Dynam. 50, 717-733. https://doi.org/10.1007/s00382-017-3639-4

Banihabib, M. E., Hasani, K., Massah, A. R., 2016. A framework for the assessment of reservoir operation adaption to climate change in an arid region. J. Glob. Warming. 9: 286-305. https://doi.org/10.1504/IJGW.2016.075446

Gohari, A., Bozorgi, A., Madani, K., Elledge, J., Berndtsson, R., 2014. Adaptation of surface water supply to climate change in Central Iran. J WATER CLIM CHANGE. 5, 391-407. https://doi.org/10.2166/wcc.2014.189

Gohari, A., Eslamian, S., Abedi-Koupaei, J., Bavani, A. M., Wang, D., Madani, K., 2013. Climate change impacts on crop production in Iran's Zayandeh-Rud River Basin. SCI TOTAL ENVIRON. 442, 405-419. https://doi.org/10.1016/j.scitotenv.2012.10.029

Goodarzi, E., Dastorani, M., Massah Bavani, A., Talebi, A., 2015. Evaluation of the Change-Factor and LARS-WG Methods of Downscaling for Simulation of Climatic Variables in the Future (Case study: Herat Azam Watershed, Yazd - Iran). ECOPERSIA. 3, 833-846.

Iizumi T, Yokozawa M, Nishimori M, 2009. Parameter estimation and uncertainty analysis of a large-scale crop model for paddy rice: application of a Bayesian approach. Agric For Meteorol. 149, 333– 348. https://doi.org/10.1016/j.agrformet.2008.08.015

Jakeman, A. J., Hornberger, G. M., 1993. How much complexity is warranted in a rainfall-runoff model? WATER RESOUR RES. 29, 2637-2649. https://doi.org/10.1029/93WR00877

Raftery, A. E., Gneiting, T., Balabdaoui, F., Polakowski, M., 2005. Using Bayesian model averaging to calibrate forecast ensembles. MON WEATHER REV. 133, 1155-1174. https://doi.org/10.1175/MWR2906.1

Semenov, M., Barrow, E., 2002. A Stochastic Weather Generator for Use in Climate Impact Studies: User Manual. Harpenden, Hertfordshire, UK.