A framework for the assessment of reservoir operation adaptation to climate change in an arid region

Mohammad Ebrahim Banihabib*,
Khadijeh Hasani and Ali Reza Massah Bavani

Department of Irrigation and Drainage Engineering,
University College of Abureyhan,
University of Tehran,
P.O. Box 3391653755, Tehran, Iran
Fax: +98-21-360-40906
Email: banihabib@ut.ac.ir
Email: hasani.nasim@gmail.com
Email: armassah@ut.ac.ir
*Corresponding author

Kamran Asgari

Young Researchers and Elite Club,
Khorasgan (Isfahan) Branch,
Islamic Azad University,
Isfahan, Iran
Email: kamran.asgari@gmail.com

Abstract: It is essential to assess the adaptation of reservoir operation to climate change in arid regions. The main objective of this research is to propose a framework for assessment of reservoir rule-curve (RRC) adaptation for climate change scenarios. The framework is applied to an arid zone in Iran and consists of the three models: downscaling, rainfall-runoff and reservoir optimisation models. LARS-WG is tested in 99% confidence level before to using it as downscaling model. Seven artificial neural network models are proposed, examined and compared with IHACRES to find proper rainfall-runoff model for arid zone. Current and adapted reservoir rule curves are derived by dynamic programming optimisation. The results demonstrate capability of proposed framework in assessment of adaptation and show that global warming negatively influences proposed index (water supply index) in normal and wet years, but has positive influence for dry years. It also improves reservoir reliability, but it cannot restore current reliability.

Keywords: arid region; artificial neural network; ANN; climate change; adaptation; downscaling; global warming; IHACRES; rainfall-runoff model; rule curve; reservoir operation; water supply index.

Reference to this paper should be made as follows: Banihabib, M.E., Hasani, K., Bavani, A.R.M. and Asgari, K. (2016) 'A framework for the assessment of reservoir operation adaptation to climate change in an arid region', *Int. J. Global Warming*, Vol. 9, No. 3, pp.286–305.

Biographical notes: Mohammad Ebrahim Banihabib is a PhD of Water Resource Engineering, Civil Engineering from Kyushu University, Japan. Currently, he is an Associate Professor in Department of Irrigation and Drainage Engineering, University of Tehran, Iran. He had studied debris flow experimentally and numerically and proposed empirical equation for sediment transport and hydraulic roughness of high-concentrated flow, and a two-dimensional mathematical model for deposition of debris flow in floodplain. In the recent decade, he has focused on three major research topics: experimental and numerical research on debris flood control, innovative models for flood and reservoir inflow/streamflow forecasting (such as ANN and hybrid models), and strategic planning of water resources. He has involved several water engineering and water resources planning projects in Iran. He has been a member of River Engineering Committee of Standard and Technical Criteria Office of Iran Water Resources Management Company for 17 years. He is currently a Visiting Professor in Utah State University, USA.

Khadijeh Hasani is a post-graduate of Water Resource Engineering from University of Tehran, Iran. She had studied in the field of climate change and reservoir operation under climate change condition. She has involved some water resources projects in engineering companies of Iran.

Ali Reza Massah Bavani received his PhD in Water Resources Engineering from University of Tarbiat Modarres, Tehran Iran in 2006. His PhD title is 'Uncertainty analysis of climate change impacts and its effects on water resources'. From 2006 up to now, he has focused on climate change impact assessment field and he has a lot of research articles and national and international project about that. He is an Associate Professor in Tehran University and teaches climate change and associated classes. He is also team leader for the vulnerability and assessment of climate change, of Iran's third national communication to the UNFCCC.

Kamran Asgari is a PhD student of soil physics. Additionally, he is a special member of Young Research Club, Islamic Azad University, Isfahan, Iran. In recent years, he has focus on experimental and numerical research on environmental pollution, impact of usage of wastewater and using pedotransfer functions and mathematical models (such as fuzzy logic and regression tree) to forecast the soil properties. He has involved a number of research projects in Iran.

1 Introduction

Impacts of global warming and its consequences on water sources are certainly one of the most important issues which occur on a global scale (IPCC, 2001; Fujihara et al., 2008). For instance, long-term changes in precipitation and temperature patterns have effects on water resources, such as reducing runoff in some regions or early peak of flows in spring in other regions (Christensen et al., 2005; Goasian et al., 2003; Matondo et al., 2004; Motiee and McBean, 2009). Thus, changes in flow time series during the year is a new challenge in water reservoirs design and management (Anderson et al., 2008; Steele-Dunne et al., 2008). Accordingly, evaluating influence of climate change on water resources is greatly highlighted in planning and management of water resource systems (Zekâi, 2013; Felgenhauer and De Bruin, 2009).

There are studies on the assessment of climate change on water resources, but a few of them focus on the assessment of climate change on reservoir management. For example, Yao and Georgakakos (2001) examined the operation of Lake Folsom Reservoir in California using integrated forecasting-decision system. The system combines a variety of inflow forecasting models, operation curve and two CO_2 emission scenarios of climate change. The research shows that the reservoir is adaptable to climate changes (Yao and Georgakakos, 2001). In other researches, Maurer et al. (2009) and Karamouz et al. (2012) investigated effects of climate change on reliability of reservoirs using outputs of the emission scenarios A2 and B2 of GCM model. Their research indicates reduction of capacity of hydropower and water supply under climate change (Karamouz et al., 2012; Maurer et al., 2009). Study of Eum and Simonovic (2010) on three reservoirs in the Nakdongin Basin, Korea show that sensitivity to impacts of climate change decreases by increasing reservoir size. In their study, weather generator, hydrological and reservoir optimisation models and investigated reservoir reliability under two weather scenarios (wet and dry) are considered for only B1 emission scenario of five GCMs (Eum and Simonovic, 2010). Moreover, the study of Raje and Mujumdar (2010) on the effect of three emission scenarios of three GCMs on the multi-purpose Hirakude Reservoir in India shows that reservoir rules for flood control should be revised because of increasing probability of droughts. Briefly, the review of few reported studies on the climate change impact on reservoir efficiency shows that these work used 1 to 5 GCMs and up to 3 emission scenarios to assess the effect of climate change on the efficiency of reservoirs in mainly wet and semiarid regions.

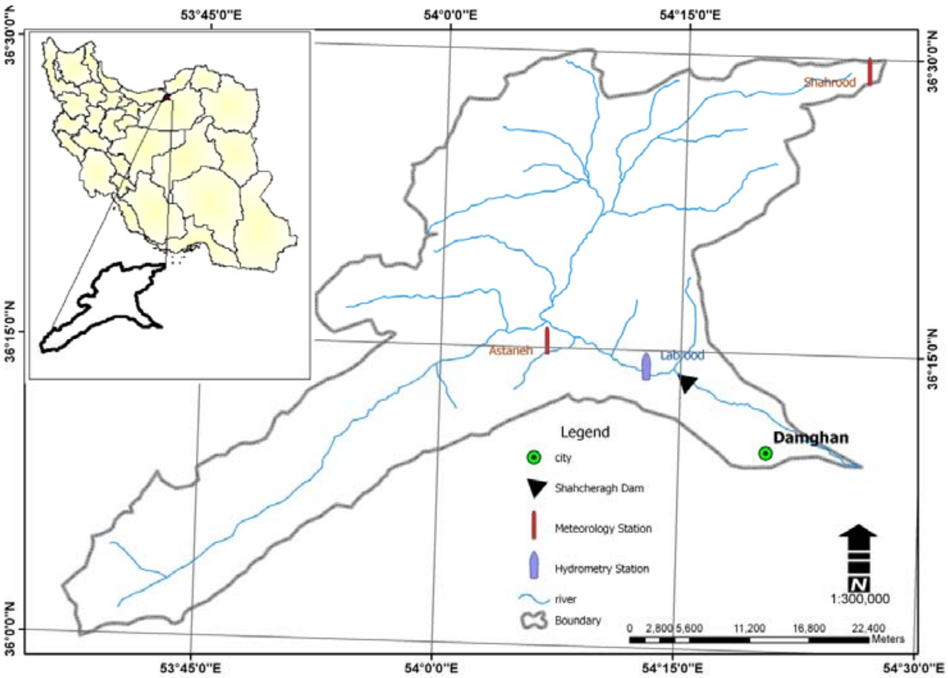
The reviewed paper reveals that climate change will affect reservoir reliability especially in semiarid and wet zones. However, more study is needed to examine how much the rule curve adaptation can increase the reliability of reservoir in arid regions. Therefore, this study is conducted to assess the impacts of climate change on reliability of a reservoir in arid zone. Considering this point, main objective of this paper is to propose a framework for adaptation of a reservoir operation in an arid zone and evaluate the reliability of rule curve adaptation.

2 Material and methods

2.1 Study area

The case study area of this research is located in arid zone of Iran in Damghan Township, Semnan Province. The case study area is a part of the arid zone of Iran (Gharekhani and Ghahreman, 2010). Shahcheraghi Dam' basin is in between 53°E to 54° 30'E longitude and 36°N to 36° 30'N latitude, 12 km north of the Damghan City (Figure 1). The area of Shahcheraghi Basin is about 1,373 km^2 with long-term average annual inflow around 17.9 MCM. Total and active volumes of reservoir are 21 and 14 MCM, respectively. Average annual rainfall and total actual evaporation are 137 mm and 1,986 mm, respectively. The case study is chosen to examine proposed framework for assessment of climate change adaptation of reservoir operation in an arid zone.

Figure 1 Shahcheraghi Dam's River Basin (see online version for colours)



2.2 Study dataset

2.2.1 Baseline period

Hydroclimatological data were used for optimisation of reservoir operation, downscaling and calibration of rainfall-runoff simulation (Figure 1). Baseline period datasets consist of daily and monthly data of river flow, precipitation, average temperature, and solar radiation for the period of 1990 to 2008. For determination of the most appropriate hydrometric stations, all the gauging stations (inside and close to the basin boundary) of the study area were evaluated. Among all stations, Labrood station (the closest station in the upstream of the reservoir) was selected as the hydrometric station for this study. This station is located on Cheshmeh-Ali River (flow data recorded from 1990 to 2008). Daily rainfall of Astaneh Station (the closest station to centre of the basin) and average, minimum and maximum temperature of Shahrood Meteorological Station were collected. Finally, solar radiation was estimated using Hargreaves Method (Allen et al., 1998). These datasets are also used for downscaling of climate change scenarios and transforming rainfall to runoff in future period.

2.2.2 Future period

In order to study the global atmospheric systems and their changes, general circulation models (GCMs) are used (IPCC, 2007). These models simulate mathematically the behaviour of the Earth's atmosphere and oceans. One of these models, which are developed by Canadian Centre for Climate Modeling and Analysis (CCCMA) is

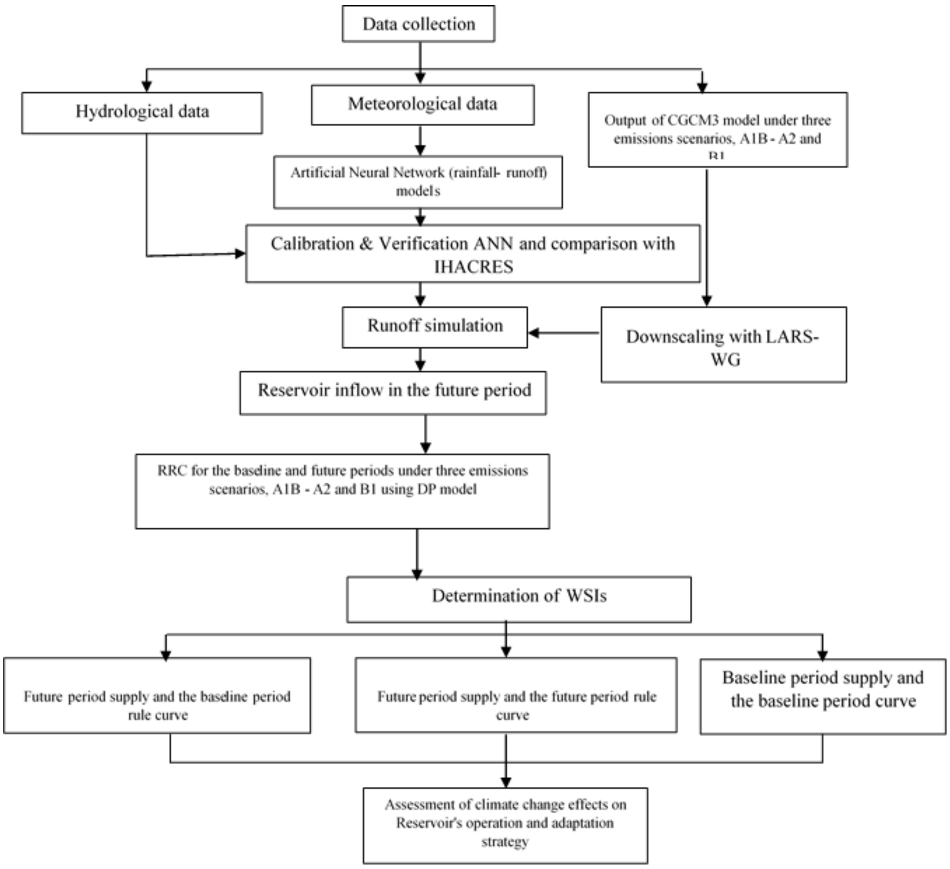
CGCM3. Its outputs were used in this research. GCMs predict climatic conditions under various emission scenarios. The scenarios are categorised into four main categories or emission (A1, A2, B1 and B2) based on Special Report on Emission Scenario (SRES) (IPCC, 2007). In most cases, these scenarios have recently been proposed for assessment of climate change in Iran (Massah Bavani, 2006; Massah Bavani et al., 2010; Karamouz et al., 2012; Ashofteh et al., 2013). Therefore, in this study three scenarios of A1B, A2 and B1 from socio-economic SRES were used to predict future (2015–2044) rainfall, air temperature and solar radiation for the study region.

2.3 Developing a framework

The proposed framework for assessing the impact of climate change on reservoir reliability consists of three sub-models:

- downscaling model for projection of future climatologic data
- hydrological model to simulate runoff of the future period
- optimisation model to determine the optimal operation of the reservoir.

Figure 2 Flowchart of proposed framework



In addition, water supply index (WSI) for measuring current and future reliability is proposed. These models are used in the proposed framework as shown in Figure 2.

2.4 Downscaling

The first part of this framework is the downscaling of outputs of climate change scenarios to local scale. Long Ashton Research Station Weather Generator (LARS-WG) model is validated in the USA, Europe and Asia (Hashmi et al., 2011; Semenov and Barrow, 1997; Semenov et al., 1998; Semenov and Stratonovitch, 2010; Fowler et al., 2007) and recommended for generating extreme meteorological event like dry and wet conditions (Semenov and Barrow, 2002; Hashmi et al., 2011). However, in this research, we tested it by observed data in 99% confidence level before using it to generate meteorological variable for future period. LARS-WG is a weather generator downscaling model that applies various statistical distributions for generating meteorological variables. This model is based on semi-empirical distribution for modelling wet and dry periods, daily precipitation and time-series of radiation. LARS-WG modelling included three stages. In the first step, regional climate was calibrated using data of long-term daily maximum and minimum temperature, rainfall and solar radiation collected from the selected station, and statistical characteristics of meteorological variables in the baseline period were determined. The second step was the evaluation of model performance where statistical characteristics of the observed and synthetic data were analysed to determine statistically significant differences. The final step in this part of the framework was to generate meteorological data (temperature, precipitation and radiation) under different climate change scenario using the outputs of CGCM3 (Semenov and Barrow, 2002).

Changes in meteorological conditions between baseline (1979–2008) and the future scenarios (2015–2044) were calculated by CGCM3 and were provided as differences for air temperature and a ratios for average long-term monthly rainfall and solar radiation. Average long-term climate change for each baseline was calculated by following formula (Jones and Hulme, 1996).

$$\Delta T_i = \overline{T}_{GCM,fut,i} - \overline{T}_{GCM,base,i} \tag{1}$$

$$\Delta P_i = \frac{\overline{P}_{GCM,fut,i}}{\overline{P}_{GCM,base,i}} \tag{2}$$

where ΔT_i and ΔP_i are the temperature and rainfall variations of climate change scenarios, respectively for $1 < i < 12$. $\overline{T}_{GCM,fut,i}$ is the long-term average of temperature (°C) forecasted by AOGCM model and $\overline{T}_{GCM,base,i}$ is long-term average temperature (°C) simulated by AOGCM model in the observation period. Data generation for rainfall has the same nomenclature.

The LARS-WG model was calibrated and verified using daily minimum and maximum temperature, solar radiation and rainfall (1990–2008) of Shahrood and Astaneh stations. The future period (2015–2044) meteorological variables are generated using climate change scenarios. The downscaled meteorological variables of the future period are used as the input of the rainfall-runoff model.

2.5 Rainfall-runoff simulation

The generated rainfall of climate scenarios was transformed into runoff with a rainfall-runoff model as a part of this framework. Identification of unit Hydrographs and Components from Rainfall, Evaporation and Streamflow (IHACRES) can be used for watersheds with limited accuracy data (Jakeman and Hornberger, 1993). This model developed by the Integrated Catchment Assessment and Management (ICAM) Centre at Australian National University, is used to simulate reservoir inflow. It has been used to a wide variety of catchment scales and climates across many continents including Asia (Karamouz et al., 2012; Ashofteh et al., 2013), Europe (Andreassian et al., 2001; Sefton and Howarth, 1998; Littlewood, 2002), Australia (Chiew et al., 1993; Ye et al., 1997; Schreider et al., 2002; Evans and Schreider, 2002; Croke and Jakeman, 2004; Croke et al., 2006), USA (Evans, 2003), and Africa (Masopha, 2001; Dye and Croke, 2003). However, Karamouz et al. (2012) reported its weakness in simulation of the peak flow. Rapid variation is a characteristic of river flow in arid zones and accurate simulation of this variation is essential for using the framework in arid zones. Consequently, seven artificial neural network (ANN) models were proposed, examined, and compared with IHACRES to find a proper model for the framework.

Reservoir inflows were simulated by ANN models and compared with the result of IHACRES model. The ANN is feed-forward multilayer perceptron (FF-MLP). In order to train and test the ANNs models, temperature, precipitation, solar radiation and monthly runoff of baseline period were used. For this reason, data were divided into two categories (80% of data for training and 20% of data for testing). Hence, the baseline period (1990–2008) was also divided into two parts (from 1990 to 2005 for training and from 2005 to 2008 for testing). The inputs of the ANN model 1 to 7 were indicated as equations (3) to (9), respectively.

$$Q_i = f\left(P_i, P_{i-1}, \ldots, P_{i-d}\right) \tag{3}$$

$$Q_i = f\left(P_i, P_{i-1}, \ldots, P_{i-d}; Tavg_i, Tavg_{i-1}, \ldots, Tavg_{i-d}\right) \tag{4}$$

$$Q_i = f\left(P_i, P_{i-1}, \ldots, P_{i-d}; Tavg_i, Tavg_{i-1}, \ldots, Tavg_{i-d}; Rs_i, Rs_{i-1}, \ldots, Rs_{i-d}\right) \tag{5}$$

$$Q_i = f\left(P_i, P_{i-1}, \ldots, P_{i-d}; Rs_i, Rs_{i-1}, \ldots, Rs_{i-d}\right) \tag{6}$$

$$\begin{aligned} Q_i = f\big(&P_i, P_{i-1}, \ldots, P_{i-d}; T\mathrm{min}_i, T\mathrm{min}_{i-1}, \ldots, T\mathrm{min}_{i-d}; \\ &T\mathrm{min}_i, T\mathrm{max}_{i-1}, \ldots, T\mathrm{max}_{i-d}\big) \end{aligned} \tag{7}$$

$$\left(Rs_i, Rs_{i-1}, \ldots, Rs_{i-d}\right) \tag{8}$$

$$\begin{aligned} Q_i = f\big(&P_i, P_{i-1}, \ldots, P_{i-d}; T\mathrm{min}_i, T\mathrm{min}_{i-1}, \ldots, T\mathrm{min}_{i-d}; \\ &Tavg_i, Tavg_{i-1}, \ldots, Tavg_{i-d}; T\mathrm{min}_i, T\mathrm{max}_{i-1}, \ldots, T\mathrm{max}_{i-d}; \\ &Rs_i, Rs_{i-1}, \ldots, Rs_{i-d}\big) \end{aligned} \tag{9}$$

where $Tavg_i$, $T\mathrm{min}_i$, $T\mathrm{max}_i$, P_i and Rs_i were monthly mean, minimum and maximum temperature, precipitation and solar radiation in month i; d is number delay of input. Number of neurons in hidden layer and number delay of input are tested 1–70 and 1–12, respectively. In addition, training function of Levenberg-Marquardt, and transfer function of hyperbolic tangent are used in ANN models. Finally, ANN models and IHACRES were compared using mean absolute relative error (MARE) and scaled root mean square error (K) as shown in equations (10) and (11):

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}\left(Q_{ms} - Q_{mo}\right)^2}{n}} \tag{10}$$

$$K = \left(\sum_{m=1}^{n} \frac{\left|Q_{mo} - Q_{ms}\right|}{Q_{mo}}\right) \Big/ \left(n\bar{Q}_{obs}\right) \tag{11}$$

where Q_{mo} and Q_{ms} are observed and simulated inflow; $\bar{Q}_{obs}$ is mean value of observed inflows; n is total number of inflow data in comparison.

2.6 Adaptation of reservoir rule curves

After generating reservoir inflow for the future period, the reservoir rule curves (RRC) of baseline and future periods (adapted rule curve) were attained using data of each period for normal, dry and wet years by dynamic programming optimisation (DPO). Dynamic programming converts a multi-step decision procedure with dependent variables to a number of single variable problems using a repeated equation (Karamouz and Houck, 1987; Mays and Tung, 1992). This method has been recently improved to handle more complicated reservoir operations optimisation applications (Li et al., 2014). RRC are obtained by minimisation of an objective function [equation (12)] subject to constraints [equations (13) to (16)] by using DPO as follows:

$$Minimise \quad Z = \sum_{t=1}^{n} loss_t\left(R_t, D_t, S_t\right) \tag{12}$$

$$S_{t+1} = S_t + Q_t - R_t - E_t - Sp_t - L_t \quad (t = 1, 2, \ldots, n) \tag{13}$$

$$S_{\min} \le S_t \le S_{\max} \qquad (t = 1, 2, \ldots, n) \tag{14}$$

$$0 \le R_t \le R_{\max} \qquad (t = 1, 2, \ldots, n) \tag{15}$$

$$S_t, D_t, L_t, R_t \ge 0 \qquad (t = 1, 2, \ldots, n) \tag{16}$$

where the loss function, $loss_t$, is a function of R_t, D_t, and S_t, release from, water demand from, and storage of the reservoir in month t, respectively; Q_t, E_t, Sp_t and L_t are reservoir inflow, evaporation, spilled water and seepage from reservoir (in MCM) in month t; $S_{\min}$ and $S_{\max}$ and $R_{\max}$ are minimum and maximum storage of reservoir (MCM) and $R_{\max}$ is maximum outlet of reservoir in month (MCM); n is number of months in each of baseline and future periods. The baseline and future RRC from DPO were assessed for reservoir reliability with a WSI to reveal improvement of reservoir reliability through adaptation.

2.7 Assessment of the adaptation

In the final step of the framework, performance of adaptation was examined by computing WSI [equation (17)]. The proposed index shows the ratio of supplied water to demand in each studied period.

$$WSI = \frac{\sum_{t=1}^{n} R_t - \sum L}{\sum_{t=1}^{n} D_t} \tag{17}$$

where

$$\sum L = \frac{1}{n} \sum_{i=1}^{N} Def_i \tag{18}$$

$$if \quad S_{t+1} > S\max \quad then \quad Sp_t = S_{t+1} - S\max \quad t = 1, 2, \ldots, n \quad else: Sp_t = 0 \tag{19}$$

$$if \quad S_{t+1} < S\min \quad then \quad Def_t = S\min - S_{t+1} \quad t = 1, 2, \ldots, n \quad else: Def_t = 0 \tag{20}$$

where Def_i is water shortage in month t using the rule curves of month in baseline and future periods. To assess the impact of adaptation, WSIs are determined and compared for the application of the rule curve of both baseline and three future scenarios (A1B, A2 and B1). Thus, seven WSIs were defined for three conditions of dry, wet and normal years as shown in Table 1.

Table 1 Definition of WSIs

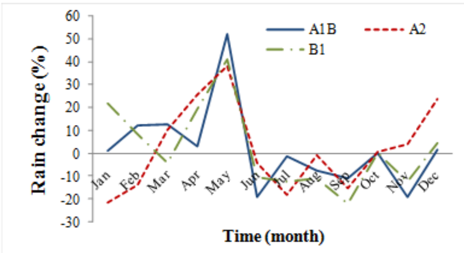
Index	*Applied rule curve*	*Applied period and scenario*	*Purpose*
$WSI_{B,B}$	Baseline	Baseline	To determine WSI for current condition
$WSI_{B,A1B}$	Baseline	Future period A1B	To determine WSI for A1B scenario without adaptation
$WSI_{B,A2}$	Baseline	Future period A2	To determine WSI for A2 scenario without adaptation
$WSI_{B,B1}$	Baseline	Future period B1	To determine WSI for B1 scenario without adaptation
$WSI_{A1B,A1B}$	Future period A1B	Future period A1B	To determine WSI for A1B scenario with adaptation
$WSI_{A2,A2}$	Future period A2	Future period A2	To determine WSI for A2 scenario with adaptation
$WSI_{B1,B1}$	Future period B1	Future period B1	To determine WSI for B1 scenario with adaptation

3 Results and discussion

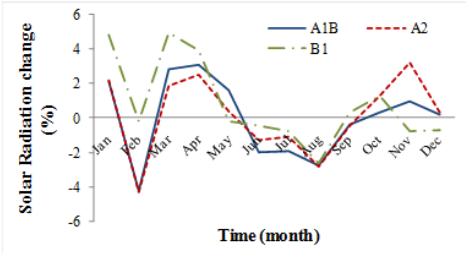
3.1 Climate change impact on meteorological variables

The studied scenarios revealed that global warming has more impact on rainfall and temperature than solar radiation (Figure 3). The greatest increase of monthly rainfall occurred on May under all the three scenarios. However, rainfall under A1B had the highest increase (52%) while the most reduction happened during January under the A2 scenario (–21.5%). Rainfall declined over the period of June to October under the three scenarios. In addition, the maximum temperature rose about 2.2 to 2.6°C in May (in all three scenarios) but the lowest increase of temperature happened in January under A2 and B1 (0.3 and 0.5°C). Generally, the maximum temperature rose in all months compared to the baseline period. Minimum and maximum temperatures increased similarly in all months, with 2.05°C in September under A2 scenario. In contrast, solar radiation change was relatively low and the most reductions happened in February under A1B and A2 scenarios (–4.2% and –4.3%) and in August under the B1 scenario (–4.2%). The greatest increase of solar radiation occur in April, November, and March with 3.1%, 3.2%, and 4.9% for A1B, A2, and B1 scenarios, respectively. The impact of global warming on rainfall and temperature can cause changes on river flow and need new strategies to adapt reservoir operation for changed inflows. Therefore, first, reservoir inflow in future period (after global warming impact) should be projected for the adaptation of reservoir operation.

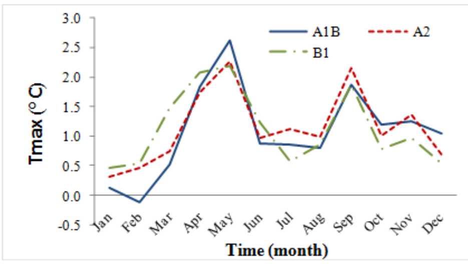
Figure 3 Changes in meteorological parameters, (a) rainfall (b) solar radiation (c) *T*max (d) *T*min (see online version for colours)



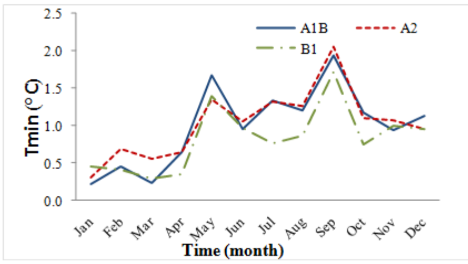
(a)



(b)



(c)



(d)

3.2 Reservoir inflow in the future period

An FF-MLP ANN model was selected from among the seven tested based on minimisation of *RMSE* and *K* (Table 2). This model (model number 6) had 12 neurons in the hidden layer, and two delays. The comparison of simulated flow hydrograph by proposed ANN model and observed one demonstrate that simulated flow hydrograph can follow observed one closely (Figure 4). When compared with the IHACRES model, this model showed a 54% and 46% reduction in *RMSE* and *K* for validation data (Table 3). The proposed ANN model was applied to forecast reservoir inflow for the climate change scenarios of the future period.

Table 2 Comparison of ANN models

ANN model	*No. of delay in inputs*	*No. of neurons in hidden layer*	*Training*		*Validation*	
			RMSE	*K*	*RMSE*	*K*
1	12	20	0.26	0.36	0.41	0.45
2	5	15	0.23	0.4	0.57	0.23
3	10	15	0.24	0.3	0.29	0.30
4	10	14	0.23	0.29	0.25	0.35
5	5	6	0.19	0.24	0.23	0.35
*6**	*2*	*12*	*0.21*	*0.21*	*0.27*	*0.26*
7	5	15	0.23	0.26	0.22	0.3

Note: *Selected model

Figure 4 Simulated flow hydrograph by proposed ANN model and observed one (see online version for colours)

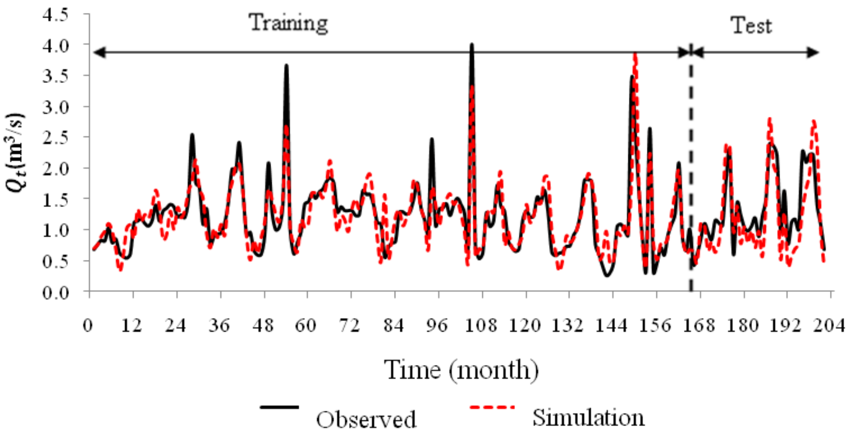


Table 3 Comparison of proposed ANN and IHACRES models

Model name	*Train*		*Validation*	
	RMSE	*K*	*RMSE*	*K*
ANN (model no. 6)	0.21	0.21	0.27	0.26
IHACRES	0.18	0.52	0.59	0.48

The forecasted inflows showed that flow alteration varies by month, but that average annual inflow to the reservoir decreased under all three scenarios with the largest reduction under the B1 scenario (4.1%). Global warming causes inflows to decrease in most months of summer and autumn and for some winter months and to increase in spring (Figure 5). Generally, due to global warming, the highest inflow increase happened on May (late spring) under scenario A1B (32.3% increase), and the highest inflow decrease happened in August (late summer) under scenario B1 (25.2% decrease). Comparing inflow with meteorological parameters (Figures 6 to 8) revealed that precipitation had direct effect on inflow in the studied scenarios and since global warming effects on rainfall, it thus impacts reservoir inflow. Comparing the changes in scenario A2 showed that the maximum decrease and increase occur during the winter and spring, respectively. Overall, the trend of changes of rainfall and inflows was very similar in A1B and B1. In addition, reductions of inflows were more than reduction of rainfall. For this reason, assessment of global warming on reservoir inflow and reservoir reliability was essential.

Figure 5 Annual and monthly flow changes under climate change scenarios

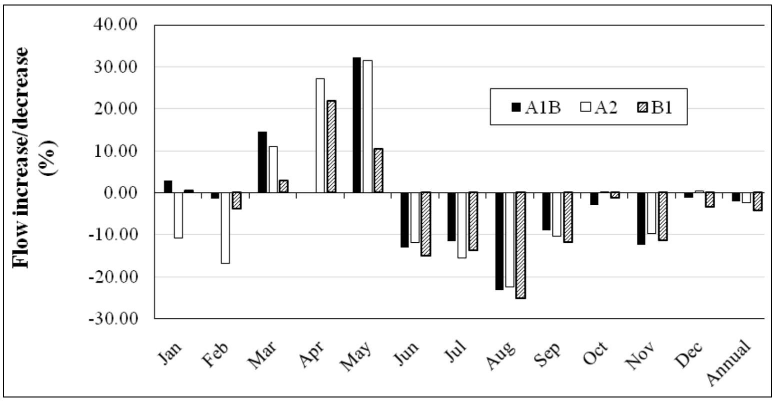


Figure 6 Changes of meteorological and hydrological parameters under scenario A1B (see online version for colours)

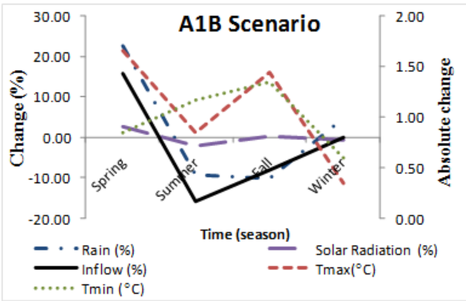


Figure 7 Changes of meteorological and hydrological parameters under scenario A2 (see online version for colours)

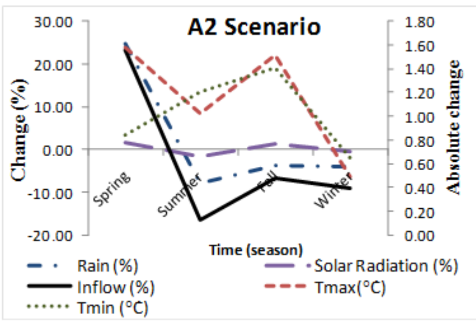


Figure 8 Changes of meteorological and hydrological parameters under scenario B1 (see online version for colours)

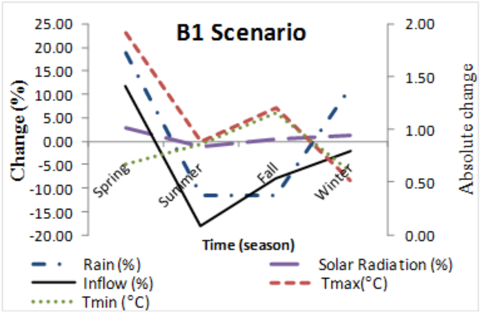


Figure 9 Observed and projected flows under climate change scenarios in normal year (see online version for colours)

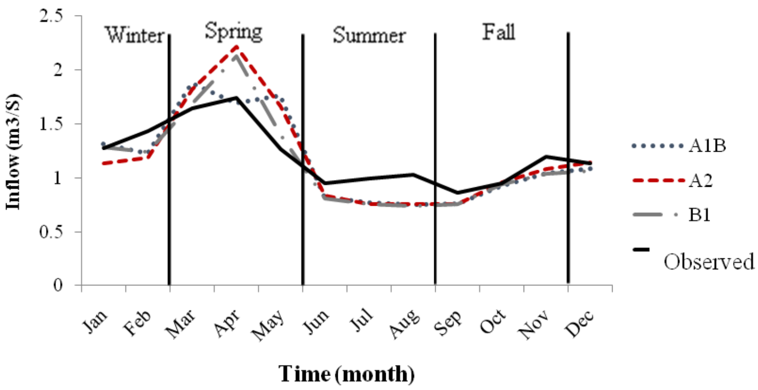
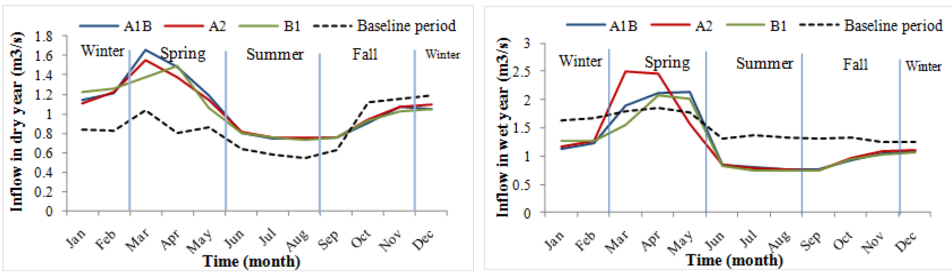


Figure 10 Observed and projected flows under climate change scenarios in dry and wet years (see online version for colours)



Comparison of reservoir inflows for the baseline and future periods showed that different trends were expected for future wet and dry years. Figure 9 indicates that global warming caused increase in flow during high-flow season (spring) and decrease in flow during low-flow season (summer). These impacts are significant in April and May (more than 20% increase) and in August (more than 20% decrease) as shown in Figure 5. Figure 10 illustrates reservoir inflow during wet and dry years over the baseline and future periods for the three scenarios. Analysing the graph of wet years showed that reservoir inflow increased by global warming during March to May (spring) and decreased during June to September (summer). However, global warming influenced inflows to decrease during October to December (fall and early of winter) in dry years and to increase in the rest of the year. Accordingly, it impacts inflow to increase in dry years and to decrease in wet years and would impact the WSI in dry, normal, and wet years differently.

3.3 Rule curves

Three RRC were produced for dry, normal, and wet yeas in baseline and each studied scenarios using the DPO model. Water release by derived RRCs were compared with demand curve to reveal deference between water supplies and demands in every month of dry, normal, and wet years of the baseline and the future periods (Figures 11 to 14). Comparison of demand and reservoir release for baseline period showed that reservoir release covers demand in dry, normal, and wet years of baseline period with reasonable deficit (Figure 11). In contrast, if RCC was not adapted for global warming, there would be significant deficit from April to July for (Figures 12 to 14). As a result, water supply will be restricted by global warming impact and hence adaptation is necessary.

Figure 11 Comparison of demand and reservoir release for baseline period (see online version for colours)

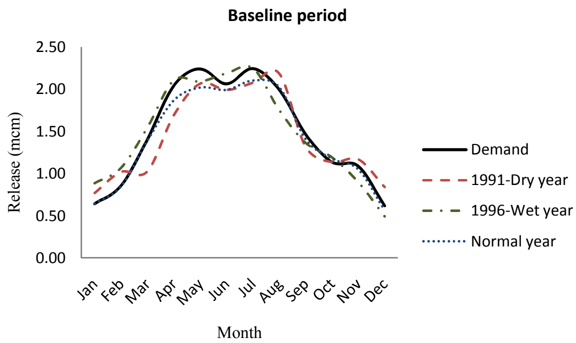


Figure 12 Comparison of demand and reservoir release for future period, A1B scenario (see online version for colours)

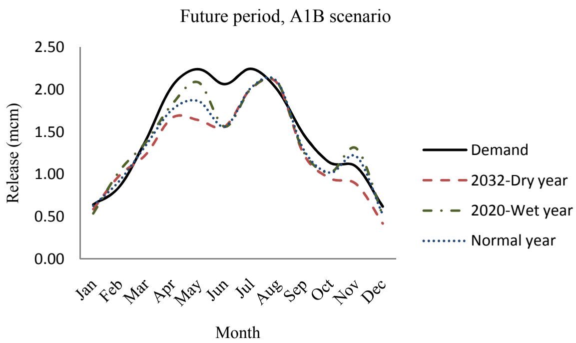


Figure 13 Comparison of demand and reservoir release for future period, A2 scenario (see online version for colours)

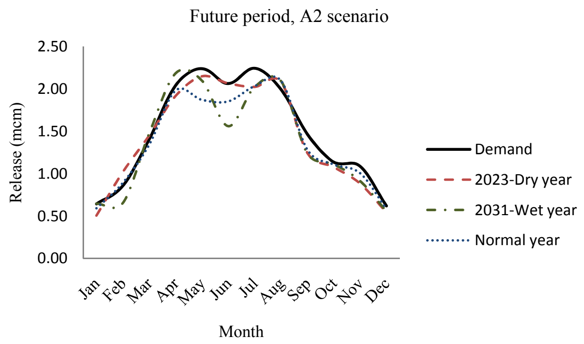
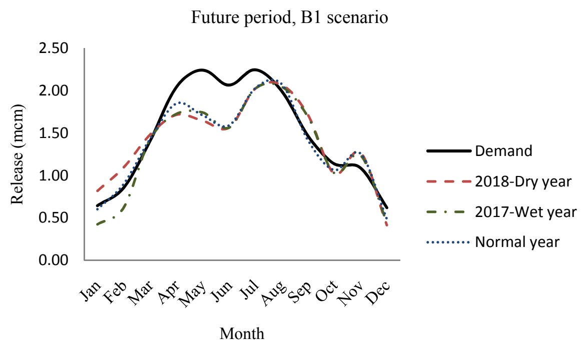


Figure 14 Comparison of demand and reservoir release for future period, B1 scenario (see online version for colours)



3.4 *Assessment of the impact and adaptation on reservoir reliability*

Reduction of reservoir inflow caused reduction of reservoir reliability by global warming in the studied scenarios (Table 4). The reservoir's WSIs were predicted to be reduced in the future with non-adapted RRCs when compared with the baseline period (about 7.7% to 16% reduction in studied scenarios in normal year). In addition, Global warming reduced inflows in the summer and fall during wet years. Thus, WSI decreased about 12.2% to 23.4% in wet year (Table 4). However, the index increased by global warming (in future period) relative to baseline period 17.5% to 18.5% in dry years of the studied scenarios. Consequently, water supply reliability for this arid-region reservoir was predicted to increase for dry years and to decrease for wet years in the future by global warming.

Comparison of adapted and non-adapted WSIs indicated significant improvement in the indices by adapting RRC for global warming, but it still is behind of the WSIs of baseline period (Table 4). WSIs improved 5.5% to 6% in normal years, 1.7% to 3.6% in wet years, and 2% to 6.9% in dry years of the studied scenarios. However, adapted WSIs were still less than current WSIs (–2.2% to –10.4% in normal year, and –8.6% to –21.7% in wet year). Global warming impacted adapted RRCs to have smaller WSI in the studied climate scenarios than baseline. As a consequence, adaptations of RRCs for the global warming may improve reservoir reliability, but it cannot restore current condition of water supply reliability.

Table 4 Water supply indices (%)

	Baseline (current)	*Future, non-adapted*			*Future, adapted*		
Period	$WSI_{B,B}$	$WSI_{B,A1B}$	$WSI_{B,A2}$	$WSI_{B,B1}$	$WSI_{A1B,A1B}$	$WSI_{A2,A2}$	$WSI_{B1,B1}$
Normal	82	68.5	74.3	66	74	79.8	71.6
Wet	100	84.7	87.8	76.6	88.5	91.4	78.3
Dry	37	54.5	55.5	55.4	56.5	61.8	62.3

4 Conclusions

There is a wealth of research on the assessment of climate change on water resources, but a few of them have focused on the assessment of climate change on reservoirs and there are no reported cases in arid zones. Thus, a study is needed to examine how rule curve adaptation may increase the reliability of reservoirs in arid regions. For this reason, this study was conducted to assess the impacts of climate change on the reliability of a reservoir in an arid zone. The proposed framework provides an assessment of RRC adaptation in an arid zone. It is applied to a reservoir located in the arid zone of Iran. In addition, since rapid variation is a characteristic of river flow in arid zones and accurate simulation of this variation is essential for assessment of the given framework in arid zones, seven ANN models are proposed, examined and compared with IHACRES to find an appropriate model for the framework. After selecting an appropriate model, it is applied to forecast reservoir inflow for the climate change scenarios of the future period. The results show reduction of inflows annually and in most months in all studied climate change scenarios. Using this result, the adaptation of RRC is examined by the proposed framework and the following main points can be concluded:

- inflow increases in dry years and it decreases in wet and normal years by global warming, it has different impact on WSI in dry, normal and wet years
- water supply is limited in studied climate change scenarios of future period compared to the baseline period and adaptation is necessary
- the impact of climate change on reservoir inflow negatively impacts reservoir WSI in normal and wet years, but positively in dry year in studied arid zone's reservoir
- adaptation of RRC for the climate change scenarios increases reservoir reliability, but it cannot restore current condition of water supply reliability.

Finally, this research shows the capability of the proposed framework to assess RRC adaptation in arid zone. The results of this research show that proposed framework can assess the global warming impact and it encourages the adaptation of RRC as a compensating solution for its negative impact. However, demand management also is needed for completely compensating of deficits.

Acknowledgements

The authors would like to appreciate Tyler King of Utah State University for editing this paper.

References

Allen, R.G., Pereira, L.S., Raes, D. and Smith, M. (1998) *Crop Evapotranspiration, (Guidelines for Computing Crop Water Requirement)*, FAO, Irrigation and Drainage paper No. 56, 290pp.

Anderson, J., Chung, F., Anderson, M., Brekke, L., Easton, D., Ejeta, M., Peterson, R. and Snyder, R. (2008) 'Progress on incorporating climate change into management of California's water resources', *Journal of Climate Change*, Vol. 89, No. 1, pp.91–108.

Andreassian, V., Perrin, C., Michel, C., Usart-Sanchez, I. and Lavabre, J. (2001) 'Impact of imperfect rainfall knowledge on the efficiency and the parameters of watershed models', *Journal of Hydrology*, Vol. 250, No. 1, pp.206–223.

Ashofteh, P.S., Bozorg Haddad, O. and Mariño, M.A. (2013) 'Scenario assessment of streamflow simulation and its transition probability in future periods under climate change', *Water Resour. Manage.*, Vol. 27, No. 1, pp.255–274.

Chiew, F.H.S., Stewardson, M.J. and Mcmahon, T.A. (1993) 'Comparison of six rainfall-runoff modelling approaches', *Journal of Hydrology*, Vol. 147, No. 1, pp.1–36.

Christensen, N.S., Wood, A.W., Visin, N., Lettenmaier, D.P. and Palmer, R.N. (2005) 'The effects of climate change on the hydrology and water resources of the Colorado River Basin', *Journal of Climate Change*, Vol. 62, Nos. 1–3, pp.337–363.

Croke, B.F.W. and Jakeman, A.J. (2004) 'A catchment moisture deficit module for the IHACRES rainfall-runoff model', *Environmental Modelling & Software*, Vol. 19, No. 1, pp.1–5.

Croke, B.F.W., Letcher, R.A. and Jakeman, A.J. (2006) 'Development of a distributed flow model for underpinning assessment of water allocation options in the Namoi River Basin, Australia', *Journal of Hydrology*, Vol. 319, No. 1, pp.51–71.

Dye, P.J. and Croke, B.F.W. (2003) 'Evaluation of streamflow predictions by the IHACRES rainfall-runoff model in two South African catchments', *Environmental Modelling & Software*, Vol. 18, No. 8, pp.705–712.

Eum, H-I. and Simonovic, S.P. (2010) 'Integrated reservoir management system for adaptation to climate change: the Nakdong River Basin in Korea', *Water Resour. Manage.*, Vol. 24, No. 24, pp.3397–3417.

Evans, J. and Schreider, S. (2002) 'Hydrological impacts of climate change on inflows to Perth, Australia', *Climatic Change*, Vol. 55, No. 3, pp.361–393.

Evans, J.P. (2003) 'Improving the characteristics of streamflow modeled by regional climate models', *Journal of Hydrology*, Vol. 284, No. 1, pp.211–227.

Felgenhauer, T. and De Bruin, K.C. (2009) 'The optimal paths of climate change mitigation and adaptation under certainty and uncertainty', *International Journal of Global Warming*, Vol. 1, Nos. 1/2/3, pp.66–88.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007) 'Review linking climate change modeling to impacts studies: recent advances in downscaling techniques for hydrological modeling', *International Journal of Climatology*, Vol. 27, No. 12, pp.1547–1578.

Fujihara, Y., Tanaka, K. and Watanabe, T. et al. (2008) 'Assessing the impact of climate change on the water resources of the Seyhan River Basin in Turkey: use of dynamically downscaling data for hydrologic simulations', *Journal of Hydrology*, Vol. 353, No. 1, pp.33–48.

Gharekhani, A. and Ghahreman, N. (2010) 'Seasonal and annual trend of relative humidity and dew point temperature in several climatic regions of Iran', *Journal of Water and Soil*, Vol. 24, No. 4, pp.636–646.

Goasian, A.K., Rao, S. and Basuray, D. (2003) 'Assessment of vulnerability and adaptation for water sector', *NATCOM Vulnerability and Adaptation Workshop on Water Resources, Coastal Zones and Human Health*, Ministry of Environment, New Delhi.

Govindaraju, R.S. (2000) 'ASCE task committee on application of artificial neural network in hydrology. artificial neural networks in hydrology, I: preliminary concepts', *Journal of Hydrology Engineering*, Vol. 5, No. 2, pp.115–123.

Hashmi, M.Z., Shamseldin, A.Y. and Melville, B.W. (2011) 'Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed', *Stochastic Environmental Research and Risk Assessment*, Vol. 25, No. 4, pp.475–484.

IPCC (2001) *The Science of Climate Change: Assessment Report of the IPCC Working Group*, edited by Houghton, J.T. et al. (Eds.) and WMO/UNEP, Climate Change 2000, Cambridge University Press, Cambridge.

IPCC (2007) *Climate Change 2007: The Synthesis Report*, Observed changes in climate and their effects, Vol. 1, p.;30.

Jakeman, A.J. and Hornberger, G.M. (1993) 'How much complexity is warranted in a rainfall-runoff model?', *Water Resour. Res.*, Vol. 29, No. 8, pp.2637–2649.

Jones, P.D. and Hulme, M. (1996) 'Calculating regional climate change time series for temperature and precipitation: methods and illustrations', *International Journal of climatology*, Vol. 16, No. 4, pp.361–377.

Karamouz, M. and Houck, M.H. (1987) 'Comparison of stochastic and deterministic dynamic programming for reservoir operating rule generation', *Journal of the American Water Resources Association*, Vol. 23, No. 1. pp.1–9.

Karamouz, M., Imen, S. and Nazif, S. (2012) 'Development of a demand driven hydro-climatic model for drought planning', *Water Resour. Manage.*, Vol. 26, No. 2, pp.329–357.

Li, C., Zhou, J., Ouyang, S., Ding, X. and Chen, L. (2014) 'Improved decomposition-coordination and discrete differential dynamic programming for optimization of large-scale hydropower system', *Energy Conversion and Management*, Vol. 84, pp.363–373.

Littlewood, I.G. (2002) 'Improved unit hydrograph characterisation of the daily flow regime (including low flows) for the River Teifi, Wales: towards better rainfall-streamflow models for regionalisation', *Hydrology and Earth System Sciences*, Vol. 6, No. 5, pp.899–911.

Masopha, M.M.F. (2001) *Development and Regionalisation of Rainfall-Runoff Models for the Semi-Arid Southern African Catchments*, Unpublished PhD thesis, Department of Civil and Environmental Engineering, Imperial College, London.

Massah Bavani, A.R. (2006) *Risk Assessment of Climate Change and Its Impact on Water Resources, Case-Study: Zayandeh Rud Basin Isfahan*, Unpublished PhD dissertation, Department of Civil Engineering, Tarbiat Modaress University, 192pp, In Farsi.

Massah Bavani, A.R., Morid, S. and Mohammadzadeh, M. (2010) 'Comparison of downscaling methods and AOGCM models in assessment of climate change effects on a regional scale', *Journal of the Earth and Space Physics*, Vol. 36, No. 4, pp.99–110.

Matondo, J.I., Peter, G. and Msibi, K.M. (2004) 'Evaluation of climate change on hydrology and water resources in Swaziland: part II', *Physics and Chemistry of the Earth*, Vol. 29, No. 15, pp.1193–1202.

Maurer, E.P., Adam, J.C. and Wood, A.W. (2009) 'Climate model based consensus on the hydrologic impacts of climate change to the Rio Lempa basin of Central America', *Hydrology and Earth System Sciences*, Vol. 13, No. 2, pp.183–194.

Mays, L.W. and Tung, Y.K. (1992) *Hydrosystems Engineering and Management*, McGraw-Hill Book Company, New York, N.Y.

Motiee, H. and McBean, E. (2009) 'An assessment of long-term trends in hydrologic components and implications for water levels in lake superior', *Journal of Hydrology Research*, Vol. 40, No. 6, pp.564–579.

Raje, D. and Mujumdar, P.P. (2010) 'Reservoir performance under uncertainty in hydrologic impacts of climate change', *Journal of Advances in Water Resources*, Vol. 33, No. 3, pp.312–326.

Schreider, S.Y., Jakeman, A.J., Letcher, R.A., Nathan, R.J., Neal, B.P. and Beavis, S.G. (2002) 'Detecting changes in streamflow response to changes in non-climatic catchment conditions: farm dam development in the Murray-Darling Basin, Australia', *Journal of Hydrology*, Vol. 262, No. 1, pp.84–98.

Sefton, C.E.M. and Howarth, S.M. (1998) 'Relationships between dynamic response characteristics and physical descriptors of catchments in England and Wales', *Journal of Hydrology*, Vol. 211, No. 1, pp.1–16.

Semenov, M.A. and Barrow, E.M. (1997) 'Use of a stochastic weather generator in the development of climate change scenarios', *Journal of Climatic Change*, Vol. 35, No. 4, pp.397–414.

Semenov, M.A. and Barrow, E.M. (2002) *LARS-WG a Stochastic Weather Generator for use in Climate Impact Studies (Version 3.0)*, User Manual, Hertfordshire, UK.

Semenov, M.A. and Stratonovitch, P. (2010) 'Use of multi-model ensembles from global climate models for assessment of climate change impacts', *Climate Research*, Vol. 41, No. 1, pp.1–14.

Semenov, M.A., Roger, J., Brooks, R.J., Barrow, E.M. and Richardson, E.W. (1998) 'Comparison of the WGEN and LARS-WG stochastic weather generators for diverse climates', *Climate Research*, Vol. 10, No. 2, pp.95–107.

Steele-Dunne, S., Lynch, P., McGrath, R., Semmler, T. et al. (2008) 'The impacts of climate change on hydrology in Ireland', *Journal of Hydrology*, Vol. 356, No. 1, pp.28–45.

Yao, H. and Georgakakos, A. (2001) 'Assessment of Folsom Lake response to historical and potential future climate scenarios: 2. Reservoir management', *Journal of Hydrology*, Vol. 249, No. 1, pp.176–196.

Ye, W., Bates, B.C., Viney, N.R., Sivapalan, M. and Jakeman, A.J. (1997) 'Performance of conceptual rainfall-runoff models in low-yielding catchments', *Water Resources Research*, Vol. 33, No. 1, pp.153–166.

Zealand, C.M., Burn, D.H. and Simonovic, S.P. (1999) 'Short term stream flow forecasting using artificial neural networks', *Journal of Hydrology*, Vol. 214, No. 1, pp.32–48.

Zekâi, S. (2013) 'Urban climate change impact and Istanbul Water Consensus', *International Journal of Global Warming*, Vol. 5, No. 2, pp.210–229.

Abbreviations

ANN	Artificial neural network
DPO	Dynamic programming optimisation
FF-MLP	Feed-forward multilayer perceptron
MARE	Mean absolute relative error
RRC	Reservoir rule curve
WSI	Water supply index

Nomenclature

A1	Is the scenario family of IPCC which defines a very rapid economic growth for the world, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies (IPCC, 2007).
A2	Is the scenario family of IPCC that defines a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing global population. Economic development is primarily regionally oriented and per capita economic growth and technological changes are more fragmented and slower than in other storylines (IPCC, 2007).
AR4	Fourth assessment report
B1	Is the storyline and scenario family of IPCC that describes a convergent world with the same global population that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives (IPCC, 2007).
B2	Is the storyline and scenario family of IPCC which defines a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is a world with continuously increasing global population at a rate lower than A2, intermediate levels of economic development, and less rapid and more diverse technological change than in the B1 and A1 storylines. While the scenario is also oriented toward environmental protection and social equity, it focuses on local and regional levels (IPCC, 2007).
CCCMA	Canadian Centre for Climate Modelling and Analysis
CGCM3	The Third Generation Coupled Global Climate Model
CO_2	Carbon dioxide
GCM	Global climate models
IHACRES	Identification of unit hydrographs and component flows from rainfall, evaporation and streamflow data
IPCC	Intergovernmental Panel on Climate Change
LARS-WG	Long Ashton Research Station Weather Generator
MCM	Million cubic meter
SRES	Special Report on Emission Scenario