Reliability Assessment of the Water Supply Systems under Uncertain Future Extreme Climate Conditions

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ABSTRACT: Increase in global mean temperature and changes in rainfall amount, pattern, and distribution over the world are all indicative of climate change events. These changes alter the hydroclimatic condition of regions as well as the availability of water resources. In this study, the data generated by 14 general circulation models (GCMs) developed under the Special Report on Emissions Scenarios (SRES) A1B, A2, and B2 are downscaled and utilized to evaluate climate change impact on the hydroclimatic system of the Karaj River basin located in central Iran. The precipitation and temperature of the study region are downscaled using the change factor approach (CFA). The study analyzes future climate data, extreme changes of future climatic conditions of precipitation, and temperature. The Hydrologiska Byråns Vattenbalansavdelning

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(HBV) model developed by the Swedish Meteorological and Hydrological Institute (SMHI) is used to simulate streamflow under extreme climate change conditions. Two different sources of uncertainty are investigated in this study. First, the model parameters uncertainty is analyzed with the Monte Carlo procedure, and then different datasets of GCMs projection are investigated under the climate of the twentieth-century climate simulation (20C3M). Results show the GCMs projections range can almost capture the historical records during the 1980s through 2000 for the Karaj basin. By applying the HBV model, considerable range of streamflow changes in the future can be projected that will affect the operation scheme of Karaj Reservoir. In this study, the system dynamics (SD) modeling approach is used to simulate the system behavior through time in an integrated fashion and evaluate its overall reliability in supplying water. The results of this study show that the runoff will decrease in the future under the climate change impact. This will result in more than 50% decrease in reliability of the Karaj Reservoir system under the extreme conditions. As a result, this research predicts that the Karaj Reservoir system will face more than 50% decrease in its reliability under the extreme conditions. Consequently, meeting the increasing water demands would be difficult and application of demand management strategies will be unavoidable.

KEYWORDS: Climate change; Rainfall–runoff model; System dynamics; Reliability

1. Introduction

The atmosphere has warmed in recent decades because of the increase in anthropogenic greenhouse gas concentrations (Alley et al. 2007). It is expected that global average surface air warming will continue during the twenty-first century and the frequency of hot extremes, heat waves, and heavy precipitation events will continuously increase. The response of the global climate system to increasing greenhouse gas concentrations is simulated with the general circulation models (GCMs), which are the most advanced tools currently available in this field. GCMs are widely applied for understanding the climate, weather forecasting, and projecting climate change.

In the past few years, various studies have investigated the hydrological impact of climate change (e.g., Boorman and Sefton 1997; Bergström et al. 2001; Gao et al. 2002; Christensen et al. 2004; Chen et al. 2007). Charlton et al. (Charlton et al. 2006) examined the impact of climate change on flood hazard and water supplies in Ireland with statistically downscaled climate data from HadCM3 (see Table 1 for model expansions). Jiang et al. (Jiang et al. 2007) investigated potential impact of human-induced climate change on the water availability in a basin in China using different monthly water balance models. Furthermore, the capability of the models in simulating the impact of hypothetical climate change scenarios were analyzed and compared. Gosain et al. (Gosain et al. 2011) used the Soil and Water Assessment Tool (SWAT) hydrological model in order to analyze the water resource of the Indian river system under the possible impact of the climate change. The severity of flood and drought is analyzed to find the vulnerable areas within the constraints of the uncertainty of climate change projections. In this study, because of the lack of a regional climate model (RCM) in the study area, different GCMs have been used to define the extreme scenarios of climate change.
<table>
<thead>
<tr>
<th>Model number</th>
<th>Model name</th>
<th>Model expansion</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CSIRO Mk3.0</td>
<td>Commonwealth Scientific and Industrial Research Organisation Mark, version 3.0</td>
<td>Australia, CSIRO Atmospheric Research, 192 x 96, L18</td>
</tr>
<tr>
<td>2</td>
<td>ECHOG-G</td>
<td>ECHAM and the global Hamburg Ocean Primitive Equation</td>
<td>Germany, Meteorological Institute of the University of Bonn, 96 x 48, L19</td>
</tr>
<tr>
<td>3</td>
<td>GFDL CM2.0</td>
<td>Geophysical Fluid Dynamics Laboratory Climate Model, version 2.0</td>
<td>United States, Geophysical Fluid Dynamics Laboratory, 144 x 90, L24</td>
</tr>
<tr>
<td>4</td>
<td>GFDL CM2.1</td>
<td>Geophysical Fluid Dynamics Laboratory Climate Model, version 2.1</td>
<td>United States, Geophysical Fluid Dynamics Laboratory, 144 x 90, L24</td>
</tr>
<tr>
<td>5</td>
<td>GISS-ER</td>
<td>Goddard Institute for Space Studies Model E-R</td>
<td>United States, NASA Goddard Institute for Space Shuttles, 72 x 46, L20</td>
</tr>
<tr>
<td>6</td>
<td>HadGEM1</td>
<td>Hadley Centre Global Environment Model, version 1</td>
<td>United Kingdom, Met Office Hadley Centre for Climate Prediction and Research, 192 x 145, L38</td>
</tr>
<tr>
<td>7</td>
<td>INM-CM3.0</td>
<td>Institute of Numerical Mathematics Coupled Model, version 3.0</td>
<td>Russia, Institute of Numerical Mathematics, 72 x 45, L21</td>
</tr>
<tr>
<td>8</td>
<td>IPSL-CM3</td>
<td>L’Institut Pierre-Simon Laplace Coupled Model, version 3</td>
<td>France, Institute Pierre Simon Laplace, 96 x 72, L19</td>
</tr>
<tr>
<td>9</td>
<td>MIROC3.2(medres)</td>
<td>Model for Interdisciplinary Research on Climate, version 3.2 (medium resolution)</td>
<td>Japan, Center for Climate System Research (The University of Tokyo), 128 x 64, L20</td>
</tr>
<tr>
<td>10</td>
<td>ECHAM5/MPI-OM</td>
<td>ECHAM5/Max Planck Institute Ocean Model</td>
<td>Germany, Max Planck Institute for Meteorology, 192 x 96, L31</td>
</tr>
<tr>
<td>11</td>
<td>MRI-CGCM2.3.2</td>
<td>Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, version 2.3.2</td>
<td>Japan, Meteorological Research Institute, 128 x 64, L30</td>
</tr>
<tr>
<td>12</td>
<td>CCSM3</td>
<td>Community Climate System Model, version 3</td>
<td>United States, National Center of Atmospheric Research, 156 x 128, L26</td>
</tr>
<tr>
<td>13</td>
<td>PCM</td>
<td>Parallel Climate Model</td>
<td>United States, National Center of Atmospheric Research, 128 x 64, L26</td>
</tr>
<tr>
<td>14</td>
<td>HadCM3</td>
<td>Hadley Centre Coupled Model, version 3</td>
<td>United Kingdom, Met Office Hadley Centre for Climate Prediction and Research, 96 x 73, L19</td>
</tr>
</tbody>
</table>
While GCMs demonstrated significant skill at the continental and hemispherical scales and incorporate a large proportion of the complexity of the global system, they are inherently unable to represent local subgrid-scale features and dynamics (Wigley et al. 1990). It is necessary to provide a logical relationship with enough accuracy between GCM outputs and what is needed in local climate impact studies. A downscaling procedure reduces the results of GCM projections to the local size to take information known at large scales and make prediction at local scales. Different downscaling methods have been used by research investigators. Their efforts comprise, but are not limited to, the statistical downscaling (SDS) and dynamic downscaling. Each methodology has its advantages and limitations. The change factor approach (CFA), the simplest and fastest among different methods, is another technique for downscaling. The advantage of this method is the processing and analysis of numerous datasets, which make this method feasible for downscaling of large number of climate change scenarios and simulations (Wilby et al. 2004). This method uses the relationships between the output of GCM experiments and local climate variables to simulate local climate characteristics in the future. Kittel et al. (Kittel et al. 1995) used this method to generate the future climate scenarios for the modeling and examine the sensitivity of the vegetation and ecological condition to the climate change in the United States. Diaz-Nieto and Wilby (Diaz-Nieto and Wilby 2005) compared and evaluated the CFA and SDS for downscaling of low flows in the River Thames under baseline (1961–90) and climate change conditions (centered on the 2020s, 2050s, and 2080s). The CFA often is used for strategic-scale assessments of climate change impact. However, they found that changes in flow associated with the SDS scenarios are generally more conservative and complex than that arising from change factors (CFs).

Klausmeyer and Shaw (Klausmeyer and Shaw 2009) used the change factor approach in order to project the shifts in the Mediterranean climates. The GCMs from the phase 3 of the Coupled Model Intercomparison Project (CMIP3) multi-model datasets are downscaled with the CFA in their research. The change factor approach, such as statistical downscaling, makes the relationship between the coarse-scale process and the local variables in stationary over time. Another assumption in CFA is that the model simulations and the “true” climate have a stationary relationship over time (Diaz-Nieto and Wilby 2005). Consequently, this method has been used often in order to the downscaling of climate change research especially in this study, while the goal is to produce multimodel ensembles in order to minimize the uncertainties of using different GCMs.

The impact of climate change on hydroclimatology of a region can be evaluated through runoff analysis. For runoff modeling, downscaled temperature and precipitation data are used in a rainfall–runoff model. In this study, the Hydrologiska Byrånns Vattenbalansavdelning (HBV)-Light hydrology model is used for rainfall–runoff modeling. The HBV-Light model was developed by the Swedish Meteorological and Hydrological Institute (SMHI) in 1976 (Bergström 1992). Seibert (Seibert 1997) simulated two basins in central Sweden with HBV-Light and used the Monte Carlo (MC) procedure to assess the uncertainty of the model parameters. Furthermore, different objective functions were used and combined with fuzzy measure in order to assess the validity of a certain parameter set.

Steele-Dunne et al. (Steele-Dunne et al. 2008) investigated the impact of climate change on hydrology in Ireland. They used HBV-Light conceptual rainfall–runoff
model in order to calculate mean winter and summer flows in several regions in Ireland. In another study, Andersson et al. (Andersson et al. 2010) used HBV and the result of the Rossby Centre Regional Climate Model (RCA3) and linked them to assess the climate change impact on Pungwa basin. The simulation of the annual rainfall shows 10% reduction in 2050. Masih et al. (Masih et al. 2010) applied the HBV model to simulate daily streamflow of the mountainous semiarid Karkheh River basin of Iran. They used hydrological similarity of drainage area, catchment characteristics, flow duration curve (FDC), and spatial proximity to simulate daily streamflow with parameters transferred from the gauges in catchment. The result of the study shows the streamflow simulation model is working well for the Karkheh River basin.

As a result, it is demonstrated in this paper that the HBV model is an appropriate model for this study as it has been used previously for other case studies especially in semiarid area. Furthermore, the capability of using the Monte Carlo procedure in this model in order to evaluate the uncertainties the model’s parameters is another advantage of this rainfall–runoff model.

Changing the natural regime of streamflow under climate change affects the amount and variability of inflow to the reservoirs as well as the reservoirs’ storage volume. To keep the reservoir operation reliability at an acceptable level, new operation policies should be implemented to determine monthly reservoirs’ outflow and storage. Because of the complexity of reservoir operation and the necessity of involvement of different end users in model development, there is a strong need to increase the confidence in simulation techniques. Therefore, in this study system dynamics, a feedback-based object-oriented simulation approach is used for modeling reservoir operations. The system dynamics (SD) modeling approach, introduced by Forrester (Forrester 1961), utilized an object-oriented modeling environment to simulate and analyze large-scale systems and behaviors of these models. Integrated analysis of the system encountered difficulty because of the complex interactions among the different components of the system. Winz et al. (Winz et al. 2009) have discussed the theoretical and practical evolution of SD in the area of water resources management over the past 50 years. Simonovic and Fahmy (Simonovic and Fahmy 1999) illustrated the use of SD in structuring water resources policy for the Nile River basin in Egypt. Ahmad and Simonovic (Ahmad and Simonovic 2000) developed an SD model for reservoir operation and evaluated the capacity of a reservoir to handle large floods. Stave (Stave 2003) developed an SD model to facilitate stakeholder participation in the water resources planning process in the Las Vegas valley in Nevada. Goharian (Goharian 2012) developed an integrated system dynamics model of the Tehran metropolitan water supply system under climate change. In this study, the developing plans are analyzed to evaluate how prepared the water supply system is to meet the future challenges. The results of this study showed that the surface water cannot support the demand by itself and groundwater resources will not be able to offset that because the supply sources of groundwater will decrease in the next 20 years as they supply the growing water demand of the Tehran metropolitan area.

In this study, the output of different GCMs under the three climate change scenarios A1, A1B, and B2 are used to project the climate change impact on the streamflow of the Karaj basin located in the central part of Iran. The different scenarios are selected based on the projection of warm, hot, wet, and dry climatic conditions of
the future in the study area. Because of the low resolution of GCM outputs, first the
temperature and rainfall data are downscaled using the change factor method and
then the HBV-Light model is used to simulate the corresponding streamflow. The
employed version of HBV-Light uses the Monte Carlo method in order to assess the
uncertainty of the model’s parameters for the calibration period. In the next step,
the water supply system of the Tehran metropolitan area is simulated to evaluate its
overall reliability in supplying water under the extreme streamflow conditions. In
this step, STELLA is used in order to model the contribution and connection of
different elements of the Karaj Reservoir system. STELLA is an object-oriented
simulation modeling software, which is produced by ISEE Systems (formerly High
Performance Systems).

The rest of this paper includes a brief description of the study area. Then the
methodology and results are discussed. Finally, a summary and conclusions are
given.

2. Study area and data

In this study, the Karaj watershed at the upstream of Karaj Reservoir located in
central Iran is the study region. Karaj Reservoir is located at 35°57’N latitude and
51°29’E longitude. The area of considered watershed is 874 km² (Figure 1). Karaj
Reservoir supplies a major part of the domestic water demand of the Tehran
metropolitan area and the required water for irrigation demand of 50 000 ha of
farms near Karaj City. The average yearly inflow to the reservoir in recent 30 years
is $472 \times 10^6$ m$^3$. The long-term mean precipitation and evaporation for the
same period are 291.78 and 445.17 mm yr$^{-1}$, respectively (Goharian 2012). Tehran’s
water supply system includes two other reservoirs (viz., the Lar and Latyan Res-
ervoirs) and the Tehran aquifer and deep wells located around Jajrood (Figure 2).
Recently, water use from deep wells in Tehran’s water supply has increased which
has affected the quality of supplied water drastically. Karaj Reservoir provides
water input for two of these water treatment plants (WTPs) with a total conveyance capacity of $11.5 \text{ m}^3 \text{s}^{-1}$. Three groups of data are used in this study as follows:

- **Historical data of hydroclimatic variables:** The historical data of precipitation, temperature, potential evaporation, and streamflow for the period of 1930–71 of the nearest synoptic and hydrometry station to Karaj Reservoir were gathered from the Iran Water Resource Management organization.

- **GCMs reference simulation data:** The simulated precipitation and temperature series for the reference period of 1971–90 for a grid including Karaj Reservoir were collected from International Panel on Climate Change (IPCC) website (http://www.ipcc-data.org/cgi-bin/ddc_nav/dataset=ar4_gcm). In this study, the data of 14 GCMs under the climate change scenarios A1, A1B, and B2 are used. The considered models and scenarios are listed in Table 1.

- **GCMs future projection data:** These data are projected for the period of 2011–30 for the same grid as data of the previous item from the IPCC website.

### 3. Methodology

In this study, a scheme is proposed for evaluating the possible impact of climate change on a basin’s streamflow. The proposed methodology is illustrated in Figure 3. First, the historical hydroclimatic data for the study region as well as the corresponding GCM simulations and projections are gathered. Then the change factor approach is used to estimate and downscale precipitation and temperature data based on the reference simulation and future projection of GCMs output for the region that includes Karaj Reservoir. The rainfall–runoff model for the study region is developed using the HBV-Light model. To evaluate the uncertainty of the model’s parameters in this study, the Monte Carlo approach is used and the best values for parameters of the model are determined. Using the estimated change
factor, the future rainfall and temperature are projected and fed into the rainfall–runoff model to simulate the future runoff of the study region. Among different future projections, those corresponding to maximum, minimum, and mean conditions are used for the runoff simulation. The details of the methodology steps are described in the following sections.

3.1. Downscaling

In this study, the CFA is used for downscaling. This method requires the GCM climate simulations and historical datasets of the subject variable of downscaling. The change factor is calculated with GCMs base-averaged monthly values of historical temperature $T_{GCM, base}$, precipitation $P_{GCM, base}$ and future data $T_{GCM, fut}$ and $P_{GCM, fut}$ as inputs; then, by adding or multiplying this factor to/by the observed precipitation $P_{Obs}$ and temperature $T_{Obs}$, an estimate of future precipitation $P_{sim}$ and temperature $T_{sim}$ are provided. The change factor technique [Equation (1)] is a simple and fast technique for processing numerous datasets with large spatial extents, making it a feasible approach for global-scale downscaling of a large number of climate simulations,

\[
\begin{align*}
T_{sim} &= T_{Obs} + \Delta T \\
\Delta T &= (T_{GCM, fut} - T_{GCM, base}) ; \\
P_{sim} &= P_{Obs} \Delta P \\
\Delta P &= \left( \frac{P_{GCM, fut}}{P_{GCM, base}} \right) ,
\end{align*}
\]

where $\Delta T$ and $\Delta P$ are monthly CFs of temperature and rainfall downscaling, respectively.
3.2. HBV-Light model

The HBV model is a conceptual model of catchment hydrology that simulates discharge using rainfall, temperature, and estimates of potential evaporation. The new version of the HBV model, HBV-Light, provides an easy to use a Windows version for research and education. Different routines in the model represent snow by a degree-day method; soil water, evaporation, and groundwater by three linear reservoir equations; and channel routing by a triangular weighting function. More descriptions of the model can be found in Bergström (Bergström 1992; Bergström 1995) and Harlin and Kung (Harlin and Kung 1992). The first step in modeling the rainfall–runoff process is using the HBV model to calibrate the model by forcing it with observed precipitation and temperature data (Bergström 1992).

The Monte Carlo approach is used for model calibration. This method allows the interaction between parameters to be taken into account as whole parameter sets vary, rather than varying individual parameters. Furthermore, simulations yield an ensemble of possible results so expected changes can be expressed as a range rather than a single result (Seibert 1997). Table 2 contains a list of the parameters, their abbreviated name in the model, units, and a reasonable range for each parameter from the prior work (Steele-Dunne et al. 2008; Booij 2005; Seibert 1997; Seibert 1999).

### Table 2. HBV-Light model parameter characteristics.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Units</th>
<th>Min value</th>
<th>Max value</th>
<th>Best values from MC simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow routine</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TT</td>
<td>Threshold temperature</td>
<td>°C</td>
<td>-2.5</td>
<td>2.5</td>
<td>2.04</td>
</tr>
<tr>
<td>CFMAX</td>
<td>Degree-day factor</td>
<td>mm °C⁻¹ day⁻¹</td>
<td>0</td>
<td>10</td>
<td>0.02</td>
</tr>
<tr>
<td>SFCF</td>
<td>Snowfall correction factor</td>
<td>—</td>
<td>0.5</td>
<td>1.5</td>
<td>1.15</td>
</tr>
<tr>
<td>CFR</td>
<td>Refreezing coefficient</td>
<td>—</td>
<td>0</td>
<td>1</td>
<td>0.54</td>
</tr>
<tr>
<td>CWH</td>
<td>Water holding capacity</td>
<td>—</td>
<td>0</td>
<td>1</td>
<td>0.60</td>
</tr>
<tr>
<td>Soil moisture routine</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FC</td>
<td>Maximum value of soil moisture storage</td>
<td>mm</td>
<td>50</td>
<td>500</td>
<td>82.14</td>
</tr>
<tr>
<td>LP</td>
<td>Soil moisture value above which actual ET equals potential ET</td>
<td>mm</td>
<td>0</td>
<td>1</td>
<td>0.096</td>
</tr>
<tr>
<td>BETA</td>
<td>Parameter that determines the relative contribution to runoff from rain or snowmelt</td>
<td>—</td>
<td>0.1</td>
<td>6</td>
<td>0.385</td>
</tr>
<tr>
<td>Response routine</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PERC</td>
<td>Maximum rate of recharge between the upper and lower groundwater boxes</td>
<td>mm day⁻¹</td>
<td>0</td>
<td>15</td>
<td>13.05</td>
</tr>
<tr>
<td>UZL</td>
<td>Threshold for Q₀ flow</td>
<td>mm</td>
<td>0</td>
<td>100</td>
<td>40.78</td>
</tr>
<tr>
<td>K0</td>
<td>Recession coefficient</td>
<td>day⁻¹</td>
<td>0.1</td>
<td>0.9</td>
<td>0.687</td>
</tr>
<tr>
<td>K1</td>
<td>Recession coefficient</td>
<td>day⁻¹</td>
<td>0.01</td>
<td>0.3</td>
<td>0.0838</td>
</tr>
<tr>
<td>K2</td>
<td>Recession coefficient</td>
<td>day⁻¹</td>
<td>0.001</td>
<td>0.1</td>
<td>0.0264</td>
</tr>
<tr>
<td>Routing routine</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MAXBAS</td>
<td>Length of triangular weighting function in routing</td>
<td>day</td>
<td>1</td>
<td>7</td>
<td>1.52</td>
</tr>
</tbody>
</table>
3.3. Measuring uncertainty

Analysis of uncertainty includes many statistical problems, especially for quantitative uncertainty analysis. Some general problems in uncertainty analysis are uncertainty factors, extrapolation models, and prediction. Uncertainty in statistical analysis is measured based on the distribution that describes the uncertainty. Uncertainty analysis of complex mathematical models often involves the use of simulation and Monte Carlo methods. The approach for assessing parameter uncertainty involves the following steps:

1) Select a distribution to describe possible values of a parameter.
2) Generate data from this distribution.
3) Use the generated data as possible values of the parameter in the model to produce output.

The MC simulation is performed by running the hydrological model $M$ multiple times, changing either the input data $x$, the parameters vectors, or even the structure of the model or a combination. In this paper we assume that the model structure and the input data are certain (correct), so mathematically this can be expressed as

$$\hat{y}_{t,i} = M(x, \theta_i); \quad t = 1, 2, \ldots, n; \quad i = 1, 2, \ldots, s,$$

where $\theta_i$ is the set of parameters sampled for the $i$th run of the MC simulation, $\hat{y}_{t,i}$ is the model output of the $t$th time step for the $i$th run, $n$ is the number of time steps, and $s$ is the number of simulations.

3.4. System dynamics

In this study, the SD approach is used to simulate the operation of the water supply system. First, the current condition and state of the system is studied with the purpose of evaluating the reliability of the water supply system. Then the relations and external factors affecting the state of water supply system are identified. This includes factors such as climate change, which includes change in rainfall, temperature, and amount of runoff as well as the effects of demographic changes, the status of development projects, and estimates of their likely impact on system resource operation. After setting out the conditions governing the dynamics of the system, the simulation and modeling of surface and groundwater resources are completed, and then a model is used to simulate the dynamics and effects and the interactions between the elements of the system over time. In this study, STELLA software is used to simulate the dynamics of the Tehran’s water supply system.

3.5. Evaluating the reliability of the system

The probability of occurrence of any failure during a certain period of time is called reliability $\text{Rel}$. There are variety of methods and ideas for evaluation of system reliability. Reliability of a system $\alpha$ in general is calculated as follows:
\[ \alpha = \text{Prob}[X_t \in S] \quad \forall t, \]  

(3)

where \( S \) is the set of all system desired outputs. In this paper, in order to calculate the reliability of the Tehran water supply system, the following equation is used:

\[ \text{Rel} = \frac{n_{\text{suc}}}{n_{\text{total}}}, \]  

(4)

where \( n_{\text{suc}} \) is the number of days in which the system performance is desired and \( n_{\text{total}} \) is the number of the days in the simulation period. Success of the system is supposed as complete supply of water demand from surface water and groundwater resources without exceeding the maximum allowable level of groundwater withdrawal.

4. Results

4.1. HBV-Light model calibration and validation

In this study, an ensemble of 10,000 parameter sets is generated by sampling from a uniform distribution within the full range of physically reasonable values for each parameter from Table 2. For each parameter set, HBV-Light is used to simulate runoff and the quality of the calibration is assessed using the Nash–Sutcliffe efficiency \( R_{\text{eff}} \) during the period of 2000–04. The Nash–Sutcliffe efficiency \( R_{\text{eff}} \) is formulated as follows:

\[ R_{\text{eff}} = 1 - \frac{\Sigma(Q_{\text{sim}}(t) - Q_{\text{Obs}}(t))^2}{\Sigma(Q_{\text{sim}}(t) - \overline{Q}_{\text{Obs}})^2}, \]  

(5)

where \( Q_{\text{sim}} \) is the simulated runoff with HBV-Light model, \( Q_{\text{Obs}} \) is the observed runoff the basin, and \( \overline{Q}_{\text{Obs}} \) is the average of observed runoff during the simulation period. Here \( R_{\text{eff}} \) compares the prediction by the model with the simplest possible prediction, a constant value of the observed mean value over the entire period. When the \( R_{\text{eff}} \) becomes equal to 1, the model simulation is a perfect fit and it means that \( Q_{\text{sim}}(t) = Q_{\text{Obs}}(t) \). When \( R_{\text{eff}} = 0 \), simulation is as good (or poor) as the constant value; otherwise, when \( R_{\text{eff}} < 0 \), the simulation of the model is a very poor fit.

The best value of parameters determined in the calibration period among 10,000 Monte Carlo simulations is shown in Table 2. These values are the selected among the ensemble of 10,000 parameter sets. Consequently, for this parameter set, HBV-Light is used to simulate runoff and the Nash–Sutcliffe efficiency \( R_{\text{eff}} \) during the period of 2001–05 is closer to 1 for this parameter set. The comparison of the observed and simulated runoff in the calibration period is given in Figure 4a. The best set of parameters has resulted in \( R_{\text{eff}} \) of 0.837 during the calibration period.

The validation results for the year of 2005–06 are illustrated in Figure 4b. The \( R_{\text{eff}} \) is about 0.926 for the validation period. Figure 4a indicates that this model simulates peak runoff, but in the recession limb streamflow reduces and the model underestimates the total runoff of the Karaj basin. It is the opposite in the validation period where the simulation model overestimates in the recession limb after a low peak and underestimates after a high peak. As a result, the Nash–Sutcliffe efficiency
of 0.92 provides an acceptable level of simulation of the streamflow for the Karaj basin.

4.2. Climate change scenarios

For comparing the projections of different GCMs, the change factor is calculated for each model under different climate change scenarios. To select the representative results for evaluating the possible range of runoff variations under climate change scenarios, 6 out of 39 projections, with minimum differences from the maximum, minimum, and the average of change factors, are selected based on the following equation:

\[
MDCF_{J_{\text{sel}}} = \min \left\{ \text{for } j = 1, 2, \ldots, n: \sum_{i=1}^{12} |CF_{a,i,j} - f(CF_{a,i})| \right\}, \quad (6)
\]

where \(f\) is a function that is considered for selection of desired projection and can be a maximum, minimum, or average. The \(J_{\text{sel}}\) is the identification of the projection.
in which its change factors have the minimum difference with the selected function (MDCF). Change factor (CF) is the downscaling step and $a$ corresponds to the variable that can be precipitation or temperature. The terms $j$ and $i$ correspond to the identification of projection and month, respectively.

Table 3 shows the results of the selected models. The results of the selected models are depicted in Figures 5a,b for precipitation and temperature, respectively. Figure 5a shows that for all models the precipitation change factors for January–April, October, and November are almost the same while the difference between the maximum and minimum change factors for each month is about 0.5. The major variations in the precipitation change factors are for July–September and November when the most models predict no precipitation for these months. MIROC3.2(medres) predicts a great amount of rainfall for these months, while it has the greater change factors compared to the other model, with the peak about 1.85 in August. Figure 5b shows all models predicted temperature increases in the future. The CCSM3 GCM predicts the maximum increase for the future period and a high value of a change factor for summers.

### 4.3. Expected future hydroclimatic conditions

Figure 6 shows the simulated streamflow with HBV-Light for the period of 2011–20 under the four selected projections of rainfall and temperature. Historical long-term average runoff from 1969 in the basin at the entrance to Karaj Reservoir is 496 mm yr$^{-1}$. The results of this paper show that, within the next 10 years, average runoff will reach 344–437 mm yr$^{-1}$, which represents a decrease in water into Karaj Reservoir due to climate change (Table 4). In this study, even under optimistic scenarios, the decrease in average annual water can be seen. Average annual runoff and runoff reduction percent in comparison to the long-term average for each scenario are shown in Table 4. With respect to the long-term average rainfall in the area, which is 291.78 mm yr$^{-1}$ from 1969, the amount of precipitation will decrease over the next 10 years. Average annual precipitation for each scenario is given in Table 4.

Furthermore, as shown in Figure 6, the trend toward decreasing amounts of runoff in the Karaj basin can be seen during next 10 years under each scenario. Although long-term effects of climate change on hydrology should be considered, this diminishing trend can be seen during these 10 years, especially after 2015. According to Figure 6, the greatest reduction in runoff has accrued under the MRI-CGCM2.3.2 (B1) scenario (Figure 6d) and the lowest reduction in runoff has accrued under the MIROC3.2 (B1) scenario (Figure 6c). Figure 6e shows the peak flow under the MIROC3.2 (B1) for the next 10 years is more than 4 mm day$^{-1}$, while for other scenarios the peak flow value is less than 4 mm day$^{-1}$.
4.4. Effects of precipitation and temperature uncertainty on streamflow

The most important issue in evaluation of the future water resources condition is to confirm that the simulation model of water availability is well calibrated. The streamflow, which is produced by the rainfall–runoff model, can be further investigated to simulate the water availability in large areas. First, the hydrological model should be validated and calibrated using the historical streamflow in order to reduce the bias between observation and simulation. Although the uncertainty in
Figure 6. Simulated streamflow under different GCMs.
model simulations is arising from different sources, in section 4.1 the model was calibrated by considering the model parameters as the source of uncertainty. By adjusting the model parameters, bias between observations and simulations is reduced; however, it cannot always be removed and it is not just attributed to the model parameters. Therefore, the other sources of uncertainty should be taken into account in simulation of future streamflow. For this purpose, first different datasets of GCMs projection are investigated under the climate of the twentieth-century climate simulation (20C3M). These datasets are compared with the observed values of the Karaj basin. Precipitation and temperature, as inputs of the rainfall–runoff model, are two major sources of uncertainty. So, the historical projections of GCMs should be investigated to see if they can capture the climatic condition for Karaj basin. Figures 7a,b show the mean monthly values of the GCM projections and the historical observed precipitation and temperature for the Karaj basin, respectively. These figures show the GCM projection range can almost capture the historical records during the 1980s through 2000. Although it seems the GCM projections underestimate temperature and precipitation during the winter, these projections can be acceptable to investigate the extreme future climatic condition of the Karaj basin and the system performance of Karaj Reservoir.

The impact of uncertainties rising from precipitation and temperature is investigated by considering them as inputs of the rainfall–runoff model in future runoff estimation. Different GCM information is used at a grid scale to simulate the streamflow of the Karaj Reservoir basin. In this study, 14 general circulation models under the Special Report on Emissions Scenarios (SRES) A1B, A2, and B2 are used to produce different precipitation and temperature sets (Table 1) and compare them at basin scale. These datasets differ with respect to the original data sources used, different numerical methods, spatial resolutions, and the downscaling method. Figures 8a,b show the ranges in mean annual precipitation and temperature for 14 GCMs under different emission scenarios, respectively.

The different precipitation datasets differ considerably in their totals, although their interannual variability is largely similar. The MIROC3.2 (B1) scenario gives substantially higher total precipitation than the others, whereas MRI-CGCM2.3.2 (B1) has the lowest total precipitation. The mean annual precipitation estimates vary from 0.95 to 2.75 mm yr$^{-1}$ for the years 2011–20.

The mean annual streamflow simulated by HBV-Light (section 4.3) forced with GCMs’ precipitation and temperature is shown in Figure 9a; it is clear that ranges in precipitation and temperature (Figure 8) translate into similar patterns of ranges in streamflow. Constant range of uncertainties in streamflow can be seen in the simulated period during 2011–20, except 2013, which has the thinner uncertainty range. As expected, the GCMs have a large uncertainty in the precipitation and temperature input, which leads to a large uncertainty in the estimated streamflow.

<table>
<thead>
<tr>
<th>Model</th>
<th>MIROC3.2 (medres) (B1)</th>
<th>MRI-CGCM 2.3.2 (B1)</th>
<th>HadGEM1 (A1B)</th>
<th>CCSM3 (A2)</th>
<th>CSIRO Mk3.0 (A1B)</th>
<th>GFDL CM2.1 (A2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum $Q_{sim}$ (mm yr$^{-1}$)</td>
<td>437.15</td>
<td>344.30</td>
<td>371.97</td>
<td>423.32</td>
<td>426.28</td>
<td>412.7</td>
</tr>
<tr>
<td>Runoff reduction (%)</td>
<td>11.9</td>
<td>30.6</td>
<td>25</td>
<td>14.7</td>
<td>14.0</td>
<td>16.8</td>
</tr>
<tr>
<td>Sum $P$ (mm yr$^{-1}$)</td>
<td>281</td>
<td>230</td>
<td>266</td>
<td>270</td>
<td>277</td>
<td>268</td>
</tr>
</tbody>
</table>
In general, for all scenarios the precipitation uncertainty is translated into discharge uncertainty. However, there are some clear seasonal differences. Figure 9b shows that the relative uncertainty in summer streamflow is lower than in winter.

(Figure 9a). In general, for all scenarios the precipitation uncertainty is translated into discharge uncertainty. However, there are some clear seasonal differences. Figure 9b shows that the relative uncertainty in summer streamflow is lower than in winter.

Figure 7. The comparison of the observed climate values with GCMs projections from 1980 to 2000: (a) precipitation and (b) temperature.
4.5. System dynamics simulation results

During the simulation of the SD model process, certain steps are taken throughout. At the end of each step, the system variables denoting the state of the system are updated to represent the consequences resulting from the previous simulation step. Initial conditions are needed for the first time step. In determining the allocation policies of using water resources for different purposes, the higher priority is given to the drinking water supply for Tehran. According to the structural and hydrological limitations of available surface water resources, the priorities are needed to supply water from the groundwater up to the maximum allowable level.

Figure 8. Mean annual climate projections for GCMs datasets, 2011–20: (a) precipitation and (b) temperature.
The Karaj Reservoir system, which includes Karaj Reservoir and water treatment plants 1 and 2, is presented in Figure 10. This diagram depicts the key elements influencing water supply and demand in the Karaj Reservoir system. The arrows denote interaction between elements. The element’s feedback loops could have either reinforcing (positive) impact, which indicates the variable (250 \times 10^6 \text{m}^3 \text{yr}^{-1}). The Karaj Reservoir system, which includes Karaj Reservoir and water treatment plants 1 and 2, is presented in Figure 10. This diagram depicts the key elements influencing water supply and demand in the Karaj Reservoir system. The arrows denote interaction between elements. The element’s feedback loops could have either reinforcing (positive) impact, which indicates the variable

Figure 9. The streamflow uncertainty based on GCMs projection and rainfall-runoff simulation for 2011–20: (a) mean annual streamflow and (b) mean monthly streamflow.
at the tail of arrow caused a change in the variable at the head of the arrow in the same direction, or balancing (negative) impact, which means the opposite to the above. Balancing feedback loops brings stability to a system. Inflow to the reservoir increases the Karaj volume, the requested municipal and irrigation demand increases the outflow from the reservoir, and more treated water increases the supply of water from reservoir. So, all elements in this module have the positive feedback, except the feedbacks of “supply Karaj” and “withdrawal Karaj” on “deficit Karaj” and “deficit 2 Karaj,” respectively. In Figure 10, “deficit” shows the difference between supply and demand water. As a result, increasing the supply water decreases the deficit. Moreover, supplying water by the exceeded withdrawal from Karaj Reservoir will provide water for the extra deficit (deficit 2 Karaj).

Historical data are needed in order to construct the SD model through analyses of the total system and identify the model validity by historical examination. Accordingly, parameters and their relevance can be modified and confirmed. Historical examination is used to check the error between simulation and reality.
According to the data and model limitations and requirements, the daily time step is considered for simulation. The model is calibrated for a 5-yr period from 2001 to 2006. Figure 11 shows the comparison between the simulated and observed storage volume of Karaj Reservoir during the calibration period. This figure shows that the model has well simulated the operational scheme of system reservoirs.

Regarding to the change of the groundwater storage, the area of the aquifer (496 km²) and storage coefficient of 0.06, the change of groundwater level is calculated as follows in each time step:

\[ \Delta h_t = \Delta VG_t / (496 \times 0.06), \]  

where \( \Delta h_t \) is the groundwater level change and \( \Delta VG_t \) is the change of groundwater volume in day \( t \). The simulated groundwater level by dynamics model in the calibration period is given in Figure 12. This figure shows that the SD model performance in simulation of the groundwater level in the study area is acceptable. The differences between observed and simulated groundwater level are due to the lack of exact information about the Tehran groundwater system.

After the model calibration, the system performance is simulated for the period of 2011–20. Figure 13 shows the variations of the storage volume of Karaj Reservoir under MIROC3.2 (B1) and MRI-CGCM2.3.2 (B1) climate change scenarios, which correspond to the highest and lowest rate of the streamflow to the reservoir in future. The results show that the amount of water storage during this period is decreasing.

The result of simulation of the groundwater storage for the same period is shown in Figure 14. This simulation shows that the amount of groundwater storage is decreasing during this period. Using more than allowable amount of groundwater in this period is caused by the growing demand during the simulated period and shortage of water supply resources.
4.6. Evaluation of the system reliability

The reliability of the system is calculated in the daily time scale during the period of 2011–20. Figure 15 shows the variations in system reliability during the simulation period between the MIROC3.2 model for climate change scenario B1 and the MRI-CGCM2.3.2 model for climate change scenario B1. Both models provide similar behavior of reliability variations. There are some cyclic fluctuations in system reliability over the study period due to the annual seasonal variations of runoff. However, the results show that the system performance becomes more stable gradually around its average value. The simulated reliability based on the MRI-CGCM2.3.2 (B1) model is less than the values obtained based on the MIROC3.2 (B1) model, except in the first year. This is because of the greater reduction in runoff based on MRI-CGCM2.3.2 (B1) in comparison with the MIROC3.2 (B1). Furthermore, the high fluctuation in the first year shows that the system does not adapt to changes. The reverse behavior in the first is because of the higher peak of runoff based on MRI-CGCM2.3.2 (B1) in this year. The average system reliability provided based on MIROC3.2 (B1) is about 0.48 and this is about 0.35 for the case of MRI-CGCM2.3.2 (B1). Considering the first year as an expectation, there is about 10%–15% tolerance in system reliability.

All of these findings demonstrate that the system behavior is highly uncertain and it is sensitive to the assumption of future climate change scenarios; therefore, a high risk of very severe shortages could be expected and should be planned for. Consequently, in order to improve the water supply system reliability in the study area, a long-term strategy to identify the alternative water supply systems should be executed to justify major investments in the region’s water resources development. Simultaneous allocation/delivery schemes as well as storage capacity building should be developed for the demand side management spirit to increase reliability and water-use efficiency.

5. Summary and conclusions

In this paper, the extreme changes of precipitation and temperature have been studied to simulate the inflow to Karaj Reservoir and evaluate the water supply
systems’ reliability under extreme conditions. Karaj Reservoir as a major part of the Tehran water supply has been considered as the case study. To incorporate the uncertainties in climate change impact, simulated data of 14 widely used GCM models under climate change scenarios of A1B, B1, and A2 are used. The rainfall and temperature data of the study area are downscaled using the change factor method. The models that provided the extreme changes in rainfall and temperature, and models corresponding to average changes are selected to evaluate climate change impact in the study region. These models provide projections of the most optimistic and pessimistic conditions in the future as well as those that are more expected. Then, the HBV-Light conceptual model calibrated for the study area using the Monte Carlo approach was used to simulate the runoff under selected projections of future rainfall and temperature for the next 10 years. In this study, an SD-based simulation model was developed to evaluate the reliability of the Karaj water supply system under future climate changes.

Regarding the present study, there are some areas that have the potential for more analysis in future works. This study is solely focusing on investigation of the probable condition of future hydroclimatic conditions in the study area. The uncertainty of the change factor method is not covered and needs more study in the future. However, Rahman et al. (Rahman et al. 2009) used the radar data to study the spatial downscaling; an effort is made to remove as much bias as possible from actual satellite data prior to downscaling. Although the change factor method has high uncertainty, the intention is to study just the impact of climate change as
extreme conditions for future scenarios. Furthermore, in this study, due to the lack of a regional climate model (RCM) in the study area, different GCMs have been used to define the extreme scenarios of climate change.

The results of rainfall and temperature downscaling in the future show that the change factors of precipitation in different months are completely different but the uncertainties in dry months (June–September) are much higher. In months other than June–September, we have 60% fluctuation in rainfall between the most optimistic/pessimistic cases. The results show a general decrease in most cases, especially in the dry months (when rainfall is almost zero). All of the cases show an increasing temperature level that would be much higher from June to December. All of these results show a high level of uncertainty in water supply resources assessment (especially surface water resources) as well as water demand. The simulated runoff under the selected climate change data show the significant decrease in the Karaj inflow between 11% and 30% under climate change impact. The results show that despite this decrease, the runoff variability over the year is not affected.

The model MIROC3.2 (B1), which corresponds to the maximum increase in precipitation, has resulted in maximum runoff while in the minimum precipitation scenario the runoff is decreased about 3 times more than the maximum precipitation. Other scenarios (minimum and maximum temperatures) as well as the minimum and maximum precipitation scenarios predict about 15% reduction in inflow to the reservoir. Consequently, this study evaluates different GCMs to decrease the uncertainty of inflow projection. For this
purpose, a range of inflow reduction is simulated in the next 10 years for Karaj Reservoir.

The runoff reduction predictions in this study will highly impact the water supply security of the study region with a significant trend in increasing population. This has been shown in the system reliability evaluation, which decreased more than 50% in the future. This means that in more than 50% of days the system will face some level of water shortages that could result in unsustainable system performance and some measure would be necessary to improve the system’s reliability. Establishment of water resources development and supply/demand side improvement scenarios in the future and evaluation of their impact on the system’s reliability can be considered in subsequent studies. Moreover, the Iran Water Resources Management organization is responsible for control of future system operation. Managers and engineers should make new and urgent decisions in order to face the climate change impact on the water resources system, controlling the trade-off between the demand and supply of water for the Tehran metropolitan area. The result of the scenarios in this paper is a hint to other regions with similar hydroclimatology to the Karaj basin/reservoir. The extreme GCMs and SRES scenarios that are selected in this paper can be investigated more and used for sophisticated downscaling in neighbor basins such as the Latyan and Lar Reservoirs in Iran. The framework that is presented in this study can be used for other regions all over the world. The framework gives this ability to different researchers to use variety of climate models, downscaling methods, rainfall–runoff techniques, and system models.
References


