Evaluation of climate change impacts on streamflow to a multiple reservoir system using a data-based mechanistic model
Sara Nazif and Mohammad Karamouz

ABSTRACT
Recent investigations have demonstrated scientists’ consensus on the increase in global mean temperature and climate variability. These changes alter the hydro-climatic condition of regions. Investigation of surface water changes is an important issue in water resources planning as well as for the operation of reservoirs. In this study a data-based mechanistic (DBM) model has been used for daily streamflow simulation. This model is a data-driven statistical base simulation model that can take advantage of additional climate variables with time variable configurations. The model has been developed for simulation of streamflow to three reservoirs, located in central Iran, using the daily rainfall, temperature and streamflow data. Comparison of the DBM results with the autoregressive integrated moving average model, as an alternative model, shows its higher performance. To include climate change impacts in study, an artificial neural network-based statistical downscaling model is developed for rainfall and temperature downscaling. The downscaled temperature and rainfall data under climate change scenarios based on HadCM3 general circulation model outputs are used to evaluate the climate change impacts on streamflow for the 2000–2050 time horizon. The results demonstrate the considerable impact of climate change on streamflow variability with significantly different behaviour in the three adjacent basins.

Key words | climate change, DBM, rainfall, streamflow simulation, temperature

INTRODUCTION
Evaluation of climate change impacts on different components of the hydro-climate system is an important challenge in the current century. The response of the global climate system to increasing greenhouse gases concentration is simulated using general circulation models (GCMs). GCMs do not provide enough resolution to represent local sub-grid-scale features and dynamics (Wigley et al. 1990). Therefore, it is necessary to provide a logical relationship with enough accuracy between GCM outputs and what is needed in local climate change impact studies. This process is called downscaling. A variety of methods is used for this purpose including dynamic and statistical downscaling methods. Owing to the greater simplicity and successful application of statistical downscaling methods, this type of downscaling is considered in this study.

Statistical downscaling methods are classified into three groups, analogue methods, regression methods, and conditional probability approaches (Bardossy 2000) but usually a combination of these methods is used (Harpham & Wilby 2005; Wetterhall 2005). Among these methods, regression is more popular because of its simplicity and wide range of applications. Although linear regression has been most widely used (Burger & Chen 2005; Sousa et al. 2007), recently, non-linear methods have also emerged (Coulibaly et al. 2005; Coulibaly & Evora 2007; Huth et al. 2008).
Among nonlinear regression methods, most attention is paid to artificial neural networks (ANNs) for downscaling purposes because of their high capability to simulate the complex, nonlinear, and time-varying characteristics of atmospheric variables at different scales. Dibike & Coulibaly (2006) proposed a temporal neural network model for downscaling climate variability and extreme events, including daily rainfall and daily maximum and minimum temperature series. Singh & Deo (2007) presented an application of alternative forms of neural network schemes to predict average daily flows at Rajghat along the Narmada River in India. Mendes & Marengo (2010) applied temporal neural networks for downscaling daily precipitation time series for a region in the Amazon Basin. The comparison of the results with an autocorrelation statistical downscaling model shows that the neural network model significantly outperforms the statistical models. Hoai et al. (2011) proposed an empirical-statistical downscaling method for precipitation downscaling using a feed-forward multilayer perceptron (MLP) neural network. They optimized the MLP considering physical bases of the circulation of atmospheric variables. Chadwick et al. (2011) used the ANN approach to downscale GCM temperature and rainfall fields to a regional model scale over Europe. Abdellatif et al. (2013) used a combination of a generalized linear model (GLM) and ANN for downscaling daily rainfall. A two-stage process is applied, an occurrence process which uses the GLM model and an amount process which uses an ANN model trained with a Levenberg–Marquardt approach. Lu & Qin (2014) used a coupled K-nearest neighbor (KNN) and Bayesian neural network (BNN) model to downscale daily rainfall. They used KNN for determination of dry/wet day and rainfall class regarding its magnitude and BNN for prediction of rainfall amount. For more details about the different applications of ANN in downscaling, see: Giorgi & Mearns (1991); Hewitson & Crane (1992a, b, 1996); Wilby & Wigley (1997); Zorita & Von Storch (1999); Sailor et al. (1999); Olsson et al. (2001, 2004); Harpham & Wilby (2005); Sousa et al. (2007); Iliadis et al. (2007); Cannon (2007); Coulibaly & Evora (2007); Cannon (2011); Karamouz et al. (2013); and Mirhosseini et al. (2013).

After understanding climate system behavior under climate change, the climate change impacts on availability and variability of different components of the hydrologic cycle can be evaluated; in this study just surface water resources are considered. A large data set is needed for physical simulation of rainfall-runoff mechanisms which is not usually accessible and there is also a high uncertainty in estimation of model parameters. Therefore in most cases, application of data-driven models such as fuzzy theory (Özelkan & Duckstein 2001), ANN (Rajurkar et al. 2004; Remesan et al. 2009; Chua & Wong 2010) and adaptive network-based fuzzy inference system (Talei et al. 2010) is preferred for practical purposes.

Data-driven modeling techniques, such as neural networks, are commonly black-box in nature; therefore, they provide little physical insight into the dominant behavioral modes of the system, and are less robust than models with a sound physical basis. The stochastic inherent in time-series analysis allows us to generate probabilistic predictions. This provides some advantages for time series analysis over black-box modeling approaches. However, these tools can also be used within a data-based mechanistic (DBM) modeling framework (Young 1998a, b) to produce acceptable simulation models, or as a precursor to mechanistic modeling where the DBM model indicates the required parsimony of the subsequent mechanistic model. Ochieng & Otieno (2009) applied the state dependent parameter models among DBM modeling approaches for a nonlinear, stochastic dynamic system to identify the location and form of the nonlinearity in the rainfall-runoff dynamics. Romanowicz (2007) presented a DBM approach to flow modeling, with special emphasis on low flows. The model applies a stochastic transfer function approach to logarithm of flow. The main advantage of DBM over the physical and conceptual models is that there is no prior assumption about the nature of the hydrological system. Also in comparison with the other data-driven hydrologic models it uses simple mathematics, linear or nonlinear forms, for definition of the hydrologic system and uses the powerful method, the simplified recursive instrumental variable (SRIV) algorithm, to identify the model structures and associated parameter values (Chappell et al. 2006). Therefore in this study DBM is used for streamflow simulation.

In this study, a methodology is proposed to evaluate the climate change impacts on inflows to the multiple reservoir surface water supply system of Tehran, capital of Iran. As a main step of a climate change impact study, first a
downscaling model for rainfall and temperature is proposed. The proposed model uses ANNs. Then the DBM modeling approach is used to simulate the response of reservoir streamflow to climate variables. Then the downscaled climate variables are used as DBM model input to simulate the system response to climate change impacts. The methodology of the study and modeling approach are described in the following section. After that the study area is introduced and then the results of the study are discussed. Finally a summary and conclusion is given.

**METHODOLOGY**

In this study a methodology is proposed for evaluation of climate change impact on streamflow variability using the DBM approach. The proposed methodology includes three main steps: (a) development of the streamflow simulation model; (b) development of the downscaling model; and (c) application of downscaling results in the developed streamflow simulation model for evaluation of climate change impacts. For streamflow simulation, the DBM approach is used considering rainfall and temperature as model inputs. Using the temperature, the effect of snow melt, soil moisture and evapotranspiration in streamflow variations are implicitly considered. The number of hours of sunshine is also important in the above-mentioned components. However, the literature shows that this is less important in comparison with temperature. Therefore hours of sunshine is not considered in streamflow simulation. The rainfall also helps to simulate the storm effect on streamflow variations. As an alternative model, an autoregressive integrated moving average (ARIMA) model is also developed for streamflow simulation. An ANN-based statistical downsampling model is used for downsampling daily rainfall and temperature. The applied models and methods in this study are explained in the following subsections.

**Streamflow simulation**

In this study the two techniques of DBM and ARIMA are used for streamflow simulation. These techniques are briefly explained.

**DBM model**

The DBM philosophy and its application are discussed fully in Young (1998b) and Beven (2001). In the first step of the DBM modeling, the appropriate structure of the model representing the objective stochastic, dynamic system is determined with minimum prejudgment about the model structure. Then the model parameters are estimated. The general structure of a DBM model with two input variables (e.g. rainfall and temperature) is as follows:

\[
q_t = \frac{B(L)}{A(L)} A_t - \delta + \frac{C(L)}{A(L)} A_{t - \gamma} + \xi_t
\]

where the transfer function polynomials are defined as

\[
A(L) = 1 + a_1 L^{-1} + a_2 L^{-2} + \ldots + a_n L^{-n} \\
B(L) = b_0 + b_1 L^{-1} + b_2 L^{-2} + \ldots + b_m L^{-m} \\
C(L) = c_0 + c_1 L^{-1} + c_2 L^{-2} + \ldots + c_k L^{-k}
\]

\(L\) is a backward shift operator (i.e. \(L^{-2} y_t = y_{t-2}\)). \(q_t\) is the measured runoff at day \(t\); \(r_t\) is the observed rainfall, \(t_r\) is the observed temperature and \(n, m\) and \(k\) are model orders corresponding to runoff, rainfall and temperature, respectively. \(\delta\) and \(\gamma\) are model delays for rainfall and temperature, respectively, and \(\xi_t\) is the stochastic noise. \(a_i, b_i\) and \(c_i\) are model coefficients. The order of the associated transfer function is defined by the form of \([n m k \delta \gamma]\). To make the model simpler, the order of error model (the last number in brackets) has been considered to be zero in all cases of the current study.

Due to errors and uncertainties in the input and output data used for model development, using the least square method for estimation of model parameters may result in considerable bias in model simulation results (Young 1984). The simplest method proposed to deal with this challenge is using an instrumental variable (IV) that is developed based on model output. In case of considerable noise in data, the filtration mechanisms can be used for noise reduction and improvement of model parameters estimation. The developed form of IV based on this filtration is called simplified recursive instrumental variable (SRIV) (Young 1985). According to Minchin et al. (1996), this method is very effective and reduces the IV modeling error to less than 10%. Therefore this method is used in this study for model parameters estimation.
algorithm is available in CAPTAIN (www.es.lancs.ac.uk/cres/captain/) Toolbox for MATLAB. The SRIV method can be interpreted in optimal statistical terms, so providing an estimate of the parametric error covariance matrix and, therefore, estimates of the confidence bounds on the parameter estimates when the measurement noise is assumed to be white. This method provides a robust approach to model identification and estimation and has been well tested in many practical applications.

In the next step, if significant parameter variation is detected by statistical tests over the observation interval, then the time or state dependency of model parameters is analyzed. After that the physical basis of the proposed model structure for the river basin under study is controlled. Finally, the estimated model is tested in various ways to ensure that it is valid. This can involve standard statistical diagnostic tests for stochastic, dynamic models, including analysis that ensures the nonlinear behavior of the runoff has been modeled adequately (Billings & Voon 1986).

Since different structures are possible for the model, it is necessary to compare different models’ performance. In this study two criteria of the Young information criterion (YIC) and coefficient of determination are used. The YIC is formulated as follows:

\[
YIC = \ln \frac{\sigma_{\text{error}}^2}{\sigma_{\text{obs}}^2} + \ln \{\text{NEVN}\}
\]

The first term of YIC is a measure of the model efficiency, where \(\sigma_{\text{error}}^2\) is the variance in the model residuals and \(\sigma_{\text{obs}}^2\) is the variance in the observed data, and the second term, normalized error variance norm (NEVN), is a measure of the degree of over-parameterization (Young 1985, 2001). This criterion varies between \(-\infty\) and zero. The smaller value of this criterion shows less uncertainty in parameters estimation and therefore more similarity of simulation results to the observed values. The coefficient of determination varies between zero and one and closer values to one show higher compatibility of the simulated and observed values.

**ARIMA model**

ARIMA models are the most general class of models used for forecasting a stationary time series. The ARIMA model predicts future values of a time series by a linear combination of its past values and a series of errors (also known as random shocks or innovations). Lags of the series appearing in the forecasting equation are called ‘auto-regressive’ terms, lags of the forecast errors are called ‘moving average’ terms, and a time series which needs to be differenced to be made stationary is said to be an ‘integrated’ version of a stationary series. The model is generally referred to as an ARIMA(p,d,q) model where parameters p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively.

An ARIMA(p,d,q) model for streamflow simulation is formulated as follows:

\[
\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) (1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \epsilon_t
\]

where \(X_t\) is the streamflow at time step \(t\), \(\phi_i\) are the parameters of the autoregressive part, \(\theta_i\) are the parameters of the moving average part, \(L\) is the lag operator and \(\epsilon_t\) are error terms. For further information about the ARIMA modeling, see Salas et al. (1980).

**Downscaling model**

In this study an ANN model is used for downscaling rainfall and temperature data. The main steps that are followed in development of the downscaling model in this study are as follows.

**Data gathering and preparation**

The rainfall and temperature data as well as weather data generated by GCMs for climate change scenarios are gathered and prepared for further analysis. The collected data are examined for any inconsistency, missing data and jump using the application of the appropriate methods. The predictors and predictands are standardized before use in the ANN model.

**Predictor set selection**

There are large number of variables in the predictor set, therefore, it is needed to select a set of the most effective
predictions for downscaling purpose. There is a considerable redundancy in predictor data because groups of variables often change together.

In this study, stepwise regression is used to select the effective predictors. Stepwise regression uses a systematic method for adding and removing independent variables from a multilinear model regarding their statistical significance in a regression. This method integrates forward selection with a backward elimination. The procedure begins with an initial model and then compares the explanatory power of incrementally larger and smaller models. If $SSR_{l_1...l_p}$ represents the sum of squares attributable to regression when the $p$ factors $X_{l_1}, ..., X_{l_p}$ are included in the multiple regression model, $SSR_{l_1...l_p|l_1...l_p-1}$ denotes the increase in the regression sum of squares resulting from adding factor $X_{l_{p+1}}$ as follows:

$$SSR_{l_1...l_p|l_1...l_p-1} = SSR_{l_1...l_p} - SSR_{l_1...l_p-1}$$

In stepwise regression, backward elimination is performed after every forward selection step to remove redundant variables from the model. At each step, the statistical methods are used to evaluate models with and without a potential term. In this study, the $p$-value statistic is used to test models. Forward regression and backward elimination steps are repeated until no further change can be made to the model.

**Development of ANN model**

In this step, using the selected predictors, ANN models with different structures are developed for downscaling. The following criteria are used for comparison of models performance

$$CE = \frac{1}{n} \sum_{i=1}^{n} (O_i - S_i)^2 \sum_{i=1}^{n} (O_i - \bar{O})^2$$

$$R = \sqrt{\frac{\sum_{i=1}^{n} (O_i - \bar{O})^2 - \sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}}$$

$$MBE = \frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)$$

where $O_i$ and $S_i$ are observed and simulated rainfall values in month $i$, respectively, and $\bar{O}$ is the mean value of observed monthly rainfall. CE, coefficient of efficiency, provides a measure of the proportion of the initial variance accounted for by the model that ranges from $-\infty$ at worst to 1 for a perfect correlation. $R$, correlation coefficient, provides the variability measure of data simulated by the models, of which a near 1 value indicates a good model performance. MBE, mean bias error, indicates whether the observed concentrations are overestimated (positive values) or underestimated (negative values).

**CASE STUDY**

In this study the impact of climate change on surface water resources of Tehran, capital of Iran, is simulated. Three reservoirs, namely, Karaj, Latyan and Lar, are the main surface water resources supplying the domestic water demand of Tehran (Figure 1) with about 2.5 million cubic meters (MCM) water consumption per day. This region has experienced severe water shortages in recent years. Therefore it is important to investigate climate change impacts on water resources availability in the region. A brief summary of the flow and watershed characteristics of these reservoirs is given in Table 1. It should be said that there is no zero data in the three reservoirs’ streamflow.

The historical climatic data of rainfall and temperature, and river streamflow are needed for rainfall-runoff modeling. Because the rainfall and temperature variations over the studied basins follow the same patterns (the correlation coefficient of rainfall and temperature series of different stations in each basin is more than 95%), the climatic data at the entrance of reservoirs are used as representative of the basin climate. The climatic data as well as the historical streamflow records are gathered from Iran Water Resources Management Organization for the period given in Table 1.

Furthermore, GCM outputs as rainfall and temperature predictors are required. The climatic outputs of GCM HadCM3 for A2 and B2 climate change scenarios were used for rainfall and temperature projection in future under climate change impacts. Both of these scenarios were emphasized for local identities. For more information
on these climate change scenarios, see Intergovernmental Panel on Climate Change (IPCC 2000).

The required information was obtained from http://www.cics.uvic.ca/scenarios/sdsm/select.cgi for the GCM HadCM3 model. Based on the 2.5° latitude by 3.75° longitude resolution of the GCM outputs, the predictors of the grid cell between 35°–37.5° latitude and 48.75°–52.5° longitude (containing the location of the studied watersheds) was downloaded from the site. The output of this model contained 26 weather variables. The observed values of these variables and simulated outputs under the climate change scenarios were available for the period of 1961–2001, and for 1961–2099, respectively.

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>River</th>
<th>Area (km²)</th>
<th>Data period</th>
<th>Annual streamflow (MCM)</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Karaj</td>
<td>Karaj</td>
<td>874</td>
<td>1969 to 2009</td>
<td>434</td>
<td>1.17</td>
<td>1.21</td>
<td>2.22</td>
<td>7.47</td>
</tr>
<tr>
<td>Latyan</td>
<td>Jajrud</td>
<td>725</td>
<td>1991 to 2009</td>
<td>331</td>
<td>0.91</td>
<td>0.92</td>
<td>2.52</td>
<td>15.63</td>
</tr>
<tr>
<td>Lar</td>
<td>Lar</td>
<td>732</td>
<td>1984 to 2009</td>
<td>455</td>
<td>1.25</td>
<td>1.53</td>
<td>2.37</td>
<td>6.23</td>
</tr>
</tbody>
</table>

Table 1 | Characteristics of Tehran water supply reservoirs

Figure 1 | Location of the study area in Iran and three reservoirs of Karaj, Lar and Latyan watersheds.
RESULTS

DBM development

First, the input data were checked and it was revealed that there were considerable missing rainfall data in different watersheds. Therefore, only time periods with no missing data were used for model development. From June 1994, a part of Lar storage was diverted to the Latyan dam for the Tehran domestic water supply. Therefore part of the Latyan inflow is regulated flow. To provide the natural streamflow series of Latyan reservoir, the volumes of diverted flow are gathered (Figure 2) and subtracted from the Latyan inflow. The considered data periods for rainfall-runoff model calibration and validation in different watersheds regarding the missing data, are given in Table 2.

The Mann–Kendall test (Salmi et al. 2002) method is applied to evaluate the significance of the streamflow trend at the reservoirs’ influent. The resulting Z-statistics of Mann–Kendall test for the streamflow data of Karaj, Lar and Latyan dams were determined to be −0.05, −1.21 and −0.98, respectively. Although the trends of streamflow values were not statistically significant at the confidence level of 5% (the absolute values are less than the Z-statistics of confidence level of 5% which is 1.96), the negative values of the test results show a slight descending trend.

The optimal DBM model structure is determined by trial and error between [1 1 0 0 0 0] and [3 3 3 3 3 0]. The given values in the brackets show the order of \( A(L) \), \( B(L) \) and \( C(L) \), delay of rainfall and temperature and error model as described in Equations (1) and (2). For greater simplicity the error model order has been considered to be zero in all cases. On the other hand, the error model is considered to be fixed in all cases. The model structure is time independent. This means that the model parameters are fixed through time. This is because there is no significant trend in streamflow series. The YIC and coefficient of determination are calculated for each of the developed models to evaluate their simulation efficiency. The model with the higher coefficient of determination and lower YIC index has better performance. The models are ranked based on these criteria. In case of similar performance criteria, the model with the least number of parameters is preferred. The selected model structures for different reservoirs, as well as the corresponding coefficient of determination and YIC, are given in Table 3.

The scatter plots of the simulated and observed streamflow data for the three reservoirs during the model calibration period are shown in Figure 3. This figure shows that the simulated streamflow data in all reservoirs match well with the recorded data of the corresponding reservoir. Only in maximum streamflow values there are some differences. The maximum flows are identified in simulation series but are commonly underestimated. That can be due to the uncertainties associated with model parameters, structure and/or pertaining assumptions that could be further investigated. Special attention to this matter is
suggested in actual implementation for flood management purposes.

The observed streamflow except the extreme values fall in the 95% confidence level of simulated values which shows the acceptable performance of the developed models. The performance of the developed model in the calibration and validation periods is compared in Table 4. The closeness of the coefficient of determination in the calibration and validation period shows the lower probability of model over fit. The models’ behavior in the validation period is similar to the calibration period and the main weakness is in simulation of extreme values. In Lar watershed, in some cases, the local maximum flows are overestimated.

To provide a physical interpretation for the developed models’ structure, the time of concentration as well as frequencies of rainfall events with different durations for different watersheds, are analyzed. The results show that more than 50% of the recorded rainfall events in all three watersheds last for just one day and the percentages of 5 days and fewer rainy days in all watersheds are about 90%. The investigation of rain series also shows that commonly after each one day rain event, there is a dry day and after that another rain event starts. This has a considerable effect on the soil moisture condition of the basin which is a key factor in runoff production. This could be a reason why the rainfall and temperature effects of a maximum previous two days have provided the best result in runoff simulation over the watershed based on the selected model structure. Furthermore the dependence of the streamflow on its previous days’ values shows the variations of base flow and its interaction with groundwater.

To improve the models’ performance especially in case of extreme flows, the state dependency of the models’ structure is checked. As an example it is considered that rainfall-related parameters are a function of the previous day’s rainfall and streamflow. The performance of the models, considering the state of dependency in their structure, does not have a significant advantage over the previous simulations. Therefore, the models with fixed variables are selected for streamflow simulation in the study regions because of their structural simplicity.

### ARIMA model development

As an alternative model, the ARIMA model is used for simulation of the three watersheds streamflow. MINITAB 14 is used for this purpose. Data to be used in this model should be stationary and normal. As it was previously tested, there is no significant trend in the data; therefore the series are stationary. The normality test revealed that streamflow data do not follow the normal distribution. The one parameter Box-Cox transformation is used to normalize data. The Box-Cox transformation parameters for Karaj, Lar and Latyan reservoirs are determined to be 0.45, −0.56 and

### Table 2: Daily data durations used in DBM development for streamflow of the three watersheds, Karaj, Lar and Latyan

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Calibration</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start</td>
<td>End</td>
<td>Start</td>
</tr>
</tbody>
</table>

### Table 3: Characteristics of the selected DBMs for simulation of the studied reservoirs’ streamflow

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Selected model structure</th>
<th>Model formulation</th>
<th>YIC</th>
<th>Coefficient of determination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Karaj</td>
<td>[3 3 0 0 0]</td>
<td>( q_t = \frac{0.043 - 0.012L^{-1} - 0.008L^{-2}}{0.931L^{-1} + 0.094L^{-2} + 0.125L^{-3}} t_t + \frac{0.026 - 0.050L^{-1} + 0.024L^{-2}}{0.931L^{-1} + 0.094L^{-2} + 0.125L^{-3}} t_t^2 )</td>
<td>-4.28</td>
<td>97%</td>
</tr>
<tr>
<td>Lar</td>
<td>[2 3 2 0 0]</td>
<td>( q_t = \frac{0.010L^{-1} - 0.005L^{-2} - 0.004L^{-3}}{0.857L^{-1} - 0.131L^{-2}} t_t + \frac{0.003 - 0.002L^{-1}}{0.857L^{-1} - 0.131L^{-2}} t_t^2 )</td>
<td>-3.331</td>
<td>99%</td>
</tr>
<tr>
<td>Latyan</td>
<td>[1 3 2 0 0]</td>
<td>( q_t = \frac{0.040 - 0.006L^{-1} - 0.024L^{-2}}{0.990L^{-1}} t_t + \frac{0.028 - 0.029L^{-1}}{0.990L^{-1}} t_t^2 )</td>
<td>-5.732</td>
<td>94%</td>
</tr>
</tbody>
</table>
The normalized data are standardized to be used in ARIMA modeling. To estimate the model order, autocorrelation function (ACF) and partial autocorrelation function (PACF) diagrams of the stream flow series are developed. The investigation results on these diagrams revealed the availability of a seasonal component in the data. To remove this seasonality a differencing operator is applied to series and then ACF and PACF diagrams are developed again. As an example developed ACF and PACF for Karaj streamflow are given in Figure 4.

Regarding Figure 4, the order of AR (autoregressive) and MA (moving average) for Karaj streamflow are estimated to be less than or equal to 5 and 1, respectively. Furthermore differencing order is one and the model does not have the seasonal component. Different models with order in the determined bounds are developed and their performances in Karaj streamflow simulation are checked. Finally an ARIMA(1,1,1) model is selected considering the parsimony criteria based on the Akaike’s Information Criterion index. The model is checked to ascertain whether it satisfies the stationarity and invertibility conditions. Furthermore the normality and independency of the model residuals, through ACF and PACF plots, are checked to ensure the satisfactory performance of the model. The same procedure is followed for simulation of other reservoirs’ streamflow. The developed ARIMA model characteristics are given in Table 5.

Table 4  Performance of developed DBMs for streamflow simulation in calibration and validation periods

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Karaj</th>
<th>Lar</th>
<th>Latyan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Coefficient of determination (R²)</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>RMSE (cm)</td>
<td>0.288</td>
<td>0.077</td>
</tr>
<tr>
<td>Validation</td>
<td>Coefficient of determination (R²)</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>RMSE (cm)</td>
<td>0.353</td>
<td>0.078</td>
</tr>
</tbody>
</table>
Regarding these results it can be concluded that the DBM has resulted in higher correlation in comparison with the ARIMA models in both the calibration and validation period for all three reservoirs. The DBM performance in terms of root mean square error (RMSE) in Lar reservoir is much better than ARIMA and for Latyan they are close to each other. In the case of Karaj reservoir the ARIMA model performance based on RMSE is better than DBM; however the main advantage of DBM is in identification of extreme values which are not well determined in the ARIMA modeling approach. Due to the data preparation needed in ARIMA modeling, the number of model parameters is greater than for DBM and DBM can be used for development of long-term series for which ARIMA models cannot be used.

Downscaling rainfall and temperature

As the first step in development of the downscaling model, stepwise regression is used to select the most effective predictors with the least redundancy for downscaling rainfall and temperature. The selected predictors are given in Table 6.

An MLP ANN model with one hidden layer and different neurons is considered for downscaling purpose. The performances of different models are evaluated through indices mentioned above. The results are given in Table 7.

The developed model for Karaj watershed temperature downscaling has simulated temperature variability well; however in months June to September the standard deviation of simulated values is lower than what is observed and there are some weaknesses in simulation of low temperatures. In the case of Lar watershed, the variability range of months with low and high temperatures was not well simulated. The model performance in simulation of average and extreme temperatures in Latyan watershed is satisfactory.

In Figure 5 the simulated temperature data under two climate change scenarios of A2 and B2 for the period of 2002–2050 as well as the observed data are shown. In Karaj watershed, the temperature in cold months is increased, particularly in scenario B2, while little decrease in months with high temperature is observed. The temperature variations in Lar watershed are limited to winter months. The increase in mean values is greater in scenario A2; however the temperature variability increase in scenario B2 is higher. In Latyan watershed a slight decrease in summer months is observed. The temperature variability especially in scenario A2 is increased.

Then the ANN model is used for rainfall downscaling using the same procedure as temperature. The characteristics of the selected models are given in Table 8.
The main weakness of the Karaj rainfall downscaling model is in months 1 and 10 in which rainfall is overestimated by about 10%. The variability of downscaled data is less than in the observed series; however, the extreme events are simulated. In downscaling Lar watershed rainfall, the rainfall of months 5, 6, 8, 9 and 12 is overestimated up to 15% but the rainfall of the wettest month is about 15% underestimated. In case of Latyan reservoir, the mean values of simulated and observed values are close except for months 4 and 12. The model has not done well in simulation of extreme rainfall events especially in dry months.

The observed and simulated rainfall series under climate change impacts are compared in Figure 6. The changes in rainfall pattern of Karaj watershed are different under the two climate change scenarios but in both scenarios extreme events are increasing. In scenario A2, approximately in all months, a considerable increase in rainfall is observed and its variability pattern is not changed. In scenario B2, there is considerable increase in rainfall in April and July but in other months it is not changed or slightly decreased.

In Lar watershed considerable change in rainfall variability is observed under climate change impacts. The maximum rainfall has been moved from March to April. Rainfall in March is considerably decreased but is increased in other months. The rainfall fluctuation is increased especially in scenario A2. The rainfall in months May to October is decreased and in other months is increased in Latyan watershed for both scenarios. The percentage of rainfall increase is higher in climate change scenario B2.

It can be concluded that, although it is expected that precipitation will remain at the same level as the current monthly level, the results show a considerable increase in precipitation average in certain months.

**Simulation of reservoirs’ streamflow under climate change impacts**

Using the downscaled rainfall and temperature data and developed DBM models for the three considered watersheds, the streamflow is simulated. The results show that the streamflow in all three reservoirs increases significantly under climate change scenarios.

### Table 6 | Selected predictors for rainfall and temperature downscaling

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Temperature</th>
<th>Rainfall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Karaj</td>
<td>Latyan</td>
</tr>
<tr>
<td>Mean regional precipitation at 2 m</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa geopotential height</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa geopotential height</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Near surface humidity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Relative humidity at 500 hPa</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Relative humidity at 850 hPa</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Surface specific humidity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Mean sea level pressure</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td>Surface airflow strength</td>
<td></td>
<td></td>
</tr>
<tr>
<td>500 hPa airflow strength</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa airflow strength</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Surface divergence</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa divergence</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa divergence</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Surface zonal velocity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa zonal velocity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa zonal velocity</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td>Surface meridional velocity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa meridional velocity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa meridional velocity</td>
<td>×</td>
<td></td>
</tr>
<tr>
<td>Surface vorticity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa vorticity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa vorticity</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>850 hPa wind direction</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>500 hPa wind direction</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>Surface wind direction</td>
<td>×</td>
<td>×</td>
</tr>
</tbody>
</table>

× Selected predictor.

### Table 7 | Characteristics of developed models for temperature downscaling for the three reservoirs’ watersheds

<table>
<thead>
<tr>
<th>Reservoir</th>
<th>Karaj</th>
<th>Latyan</th>
<th>Lar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neurons in hidden layer</td>
<td>10</td>
<td>8</td>
<td>11</td>
</tr>
<tr>
<td>CE</td>
<td>0.89</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>R</td>
<td>0.94</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>MBE (C)</td>
<td>0.03</td>
<td>– 0.02</td>
<td>$-7.04 \times 10^{-5}$</td>
</tr>
</tbody>
</table>
watersheds, the streamflow series for the period 2002–2050 for the three reservoirs are simulated. The results in comparison with the observed values are given in Figure 7.

There are obvious changes in extreme values, range of variations and annual variability scheme of Karaj streamflow. There is a new peak flow at the end of fall in addition to the current spring peak flow. The new peak is higher in scenario A2. The streamflow of dry months is considerably increased and extreme values are higher in scenario A2.

The streamflow peak of Lar reservoir remains in May; however in other months with considerable streamflow, decrease in streamflow is observed. A small peak is observed at the end of fall. The extreme values are increased in both scenarios especially in scenario B2. The Latyan streamflow has followed its current pattern. Streamflow of all months except those with highest and lowest values is increased. The streamflow fluctuations especially in scenario B2 are increased.

The annual mean streamflow of Latyan is 331 MCM which is increased under climate change impacts to about 480 MCM in both scenarios. The intensity of dry and wet periods is considerably increased especially in scenario B2. The mean annual streamflow of Karaj is 434 MCM, which is increased to 584 MCM in scenario A2 and 514 in scenario B2. Only the streamflow of Lar is decreased from its current value of 455 MCM to 416 MCM in scenario A2 and 434 MCM in scenario B2.

The overall increase in streamflow to the reservoirs could be attributed to an increase in temperature and therefore greater evapotranspiration from the reservoirs as well as more precipitation. It seems that the activities of the hydrologic cycle elements (i.e. evaporation, precipitation) will be accelerated. Furthermore, this increase in streamflow can be in the form of floods which could not be used effectively for water supply purposes. These
gradual changes have dramatic effects on sustainable water resources planning for Tehran. Therefore to keep system stability, it is necessary to apply programs for the modification of water resources operation and allocation plans.

### SUMMARY AND CONCLUSION

In this study the climate change impact on Tehran’s surface water supply resources is evaluated. DBM techniques are employed for simulation of streamflow of the three Tehran...
reservoirs. The DBM modeling technique is a powerful data-driven technique that extends a class of widely used linear storage-based hydrological models. The main advantage of this model is its ability to incorporate different predictors and get feedback from predictand values from the previous steps. The results of the model application for the study region show its ability to simulate daily streamflow behavior regarding the variation of the climatic parameters of rainfall and temperature. The only weak point of the model performance is in simulation of small flow peaks and also some of the extreme values are underestimated.

The ANN models are used to downscale rainfall and temperature data of the study region. The climate change impact on temperature of different watersheds is also the same but there are some differences in watersheds’ rainfall response to climate change. However, the downscaling results showed considerable change especially in rainfall of months with maximum values in all watersheds. The downscaled data are used to simulate the streamflow using the developed DBM model. The simulated streamflow of different reservoirs show the different responses of studied regions. The streamflow is increasing in Karaj and Latyan watersheds but decreasing in Lar watershed. The streamflow variability will be considerably changed. To improve the performance of the Tehran water supply system, these changes should be incorporated in long-term water resources planning of these watersheds. Tehran’s water supply is currently facing major challenges due to increasing population and higher standards of living; the impact of climate change as explained in this paper could provide new insight into development of future water supply and demand management strategies.

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