Water allocation using game theory under climate change impact (case study: Zarinehrood)

Hasti Hemati and Ahmad Abrishamchi

ABSTRACT

The combined effects of climate change and growing water demand due to population growth, industrial and agricultural developments cause an increase in water scarcity and the subsequent environmental crisis in river basins, which results in conflicts over the property rights and allocation agreements. Thus, an integrated, sustainable and efficient water allocation considering changes in water resources due to climate change and change of users' demands is necessary. In this study, the drainage basin of Zarinehrood was chosen to evaluate the function of selective methods. Assessing climate change impact scenarios of the Fifth IPCC reports, e.g., RCP2.6, RCP4.5, RCP6.0 and RCP8.5, have been used. For downscaling outputs of GCMs an artificial neural network (ANN) and for bias correction a quantile mapping (QM) method have been used. Using a bargaining game and the Nash bargaining solution (NBS) with two methods, one symmetric and two AHP methods, the water available for users was allocated. Results indicate an overall increase in temperature and precipitation in the basin. In bargaining game solutions, AHP provided better utilities for players than the symmetric method. These results show that with water management programs and use of a cooperative bargaining game, water allocation can be done in an efficient way.

Key words | AHP, ANN, climate change, game theory, Nash bargaining solution, QM

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HIGHLIGHTS

- Using ANN for downscaling.
- Using QM for bias correction.
- Using game theory for allocation.
- Using AHP method for calculating negotiation power.
- Evaluating all of the methods.

INTRODUCTION

Water allocation is central to the management of water resources. Due to geographically and temporally unevenly distributed precipitation (Al Radif 1999), rapidly increasing water demands driven by the world population, effects of climate change on river flow and other stresses, and degradation of the water environment, there are increasing scarcities of water resources in many countries. Conflicts often arise when different water users (including the environment) compete for limited water supply. The need to establish appropriate water allocation methodologies and associated management institutions and policies is recognized by researchers, water planners, and governments. Many studies have been carried out in this domain, but there are still many obstacles to reaching equitable, efficient,

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and sustainable water allocations (Dinar *et al.* 1997; Syme *et al.* 1999). Alongside these conflicts, there are also indications that recent climate changes have already affected many physical and biological systems. The impact of these effects includes extreme occurrence of flooding and droughts.

Various methods and models have been used in water resources allocation, including simulation methods, optimization methods, water rights, game theory, and complex adaptive systems (Di Nardo *et al.* 2018). The water resources allocation problem usually involves various rational decision-maker interactions, and water resources allocation needs to consider multiple objectives (such as economic, social, environmental, etc.), which yields multi-objective decision-making problems. This kind of allocation model solves water resources allocation problems via optimization approaches, which reflect the indirect interaction between decision-makers, but ignore the direct interaction between decision-makers, making them impractical in real-world applications (Madani 2010). Game theory is a theory of decision-making and equilibrium during the process of direct interaction between decision-makers (Loáiciga 2004). Therefore, water resources allocation based on game theory is a promising method for reducing this deficiency. Moreover, compared with traditional water resources allocation, which only focuses on the interests of the whole society, using the game theory to study the conflict of water resources allocation allows full consideration of the influence of all decision-makers. It is recognized that there are different interests among decision-makers in the process of water resources allocation, and game theory can be used to maximize the benefits of all water users while achieving the rational allocation of water resources. Therefore, using the game theory to study the conflict of water resources allocation is more practical. In recent years, water resources allocation based on game theory has been studied and extended. Carraro *et al.* (2005) systematically expounded the application of non-cooperative negotiation theory in water resources conflict. Parrachino (2006) applied cooperative game theory to water resource issues, and their results showed that cooperation over scarce water resources was possible under various physical conditions and institutional arrangements. Madani (2010) demonstrated that the application of game theory in the field of water resources can be divided into five parts, i.e., water or benefit allocation among water users, groundwater management, transboundary water allocation, water quality management, and other types of water resources management. Dinar *et al.* (1997) divided the application of game theory in the conflict of water resources allocation into three aspects: (1) the application of non-cooperative negotiation theory in water resources allocation conflict; (2) the application of graph model in water resources allocation conflict; (3) application of Nash bargaining theory and Nash–Harsanyi bargaining theory to water resources allocation problems. In the above water resources allocation conflict research, Rogers (1969) originally applied game theory to the conflict of water resources allocation problems in transboundary river basins. In recent studies, Eleftheriadou & Mylopoulos (2008) implemented game theoretical concepts in a case study of Greek–Bulgarian negotiations on the Nestos/Mesta transboundary river. Hipel *et al.* (2011) applied the graph model of non-cooperative game to the conflict of water resources allocation, and their proposed method has been widely used. Madani & Lund (2011) traced changes in delta conflict by game theory. Kucukmehmetoglu (2012) introduced a composite method that integrates both Pareto frontier and game theory in the Euphrates and Tigris rivers. Zarghami *et al.* (2015) introduced a mathematical model which integrates both the leader–follower concept and the bargaining theory in the case of the Zarrinehrud River basin. Li *et al.* (2016) developed a generalized uncooperative planar game theory model for water distribution in a transboundary river basin. Degefu *et al.* (2016) proposed a cooperative bargaining approach for solving the water sharing problem in the Nile River basin.

The impacts that climate change may have on water availability are largely affected by water allocations and the countermeasures undertaken (IPCC 2014). Climate change is believed to cause changes both in water quantity and water quality. The prospect of these changes will help decision-makers formulate mitigation and adaptation strategies to effectively deal with the impacts posed by climate change. A variety of general circulation models (GCMs) has been developed to project climate over long-term horizons under pre-determined greenhouse gas emission scenarios. Their projections often provide the source of data used for assessing impacts of climate change in various fields, such as agriculture, water resources, and the environment. The GCM outputs are coarse in resolution (a horizontal resolution of GCM is generally about 300 km) and have the statistical characteristics of an average area rather than of a point quantity (Osborn & Hulme 1997). However, hydrological models often require regional and finer-scale projections, and this coarse resolution constrains the usefulness of GCMs in climate change impact studies. In several previous studies (Mimikou *et al.* 2000; Stone *et al.* 2001; Booty *et al.* 2005), future climate scenarios were generated by adding predicted changes by GCMs into baseline scenarios. Dibike & Coulibaly (2007) argued that the simple shifts in climate variables were very crude. In order to utilize GCM outputs in regional studies, two approaches, namely, dynamic downscaling, such as using regional circulation models (RCMs), and statistical downscaling, have been developed. Murphy (1999) indicated that there is no clear difference in the performance level between these two techniques in terms of downscaling monthly climate data. Arnbjerg-Nielsen & Fleischer (2009) studied the impact of climate change and identified suitable adaptation strategies due to flooding posed by climate change from an economic perspective. Two types of models, namely, deterministic (i.e., conceptual and physically based) models and data-driven or statistical models (e.g., artificial neural networks (ANNs)) have been implemented to evaluate the impacts of climate change on water resources. As an alternative approach to deterministic models, the ANN approach has been employed in various fields including hydrology and water resources (Govindaraju 2000). Some of the advantages of using a data-driven modeling approach include needing less data and less extensive user expertise and knowledge into physical processes. In predicting event-based stormwater runoff quantity, the reliability of the ANN approach has been proven in several studies. For example, Minns & Hall (1996) and Chua *et al.* (2008) demonstrated the ability of ANNs to model event-based rainfall-runoff by using synthetically generated data and experimentally collected data, respectively. In addition, Jain & Prasad Indurthy (2003) compared deterministic models and statistical models including ANNs for predicting event-based rainfall-runoff. They found that ANNs consistently outperformed the other models. Also, Bai *et al.* (2015) used a multiscale deep feature learning method to predict inflows to the Three Gorges reservoir along the Yangtze River between Chongqing and Hubei Province, China.

The objective of this paper is to analyze water allocation in Zarinehrood river basins, Iran, considering the impact of climate change on its hydrologic parameters. Assessing climate change impact, an ANN for downscaling outputs of GCMs and for bias correction a quantile mapping (QM) method have been used. Then, considering some assumptions for predicting future demands, a water resources management program has been used to assess the water available for allocating to users. Using a bargaining game and the Nash bargaining solution (NBS) with two methods, one symmetric and the other AHP method, the water available for users has been allocated.

METHODOLOGY

Artificial neural network

An ANN is a computational tool based on the biological processes of the human brain (Sudheer *et al.* 2003). Its capability to predict output variables by using a series of interconnected nodes that recognize relations between input and output variables makes ANN models powerful tools for hydrologic analyses (Mutlu *et al.* 2008). Model inputs are weighted and passed to internal nodes in hidden layers, which develop functions for output (Figure 1). There can be one or more of these hidden layers between the input and output. Compared with conventional rainfall-runoff models, ANN models require fewer parameters but still provide reliable results in hydrological forecasting (Riad *et al.* 2003). The complexity of physical processes involved in the conventional hydrologic models has triggered the increasing use of ANN models (Rezaeianzadeh *et al.* 2013) for hydrologic predictions. Several studies have been conducted that show the advantages of using ANN models for rainfall-runoff modeling in terms of the required data to establish rainfall-runoff relations, and research continues in developing the best data and methods for these applications (Shamseldin 1997; De Vos & Rientjes 2005). Developing ANN models begins with the evaluation and determination of suitable input variables. Data selection for suitable model performance mostly

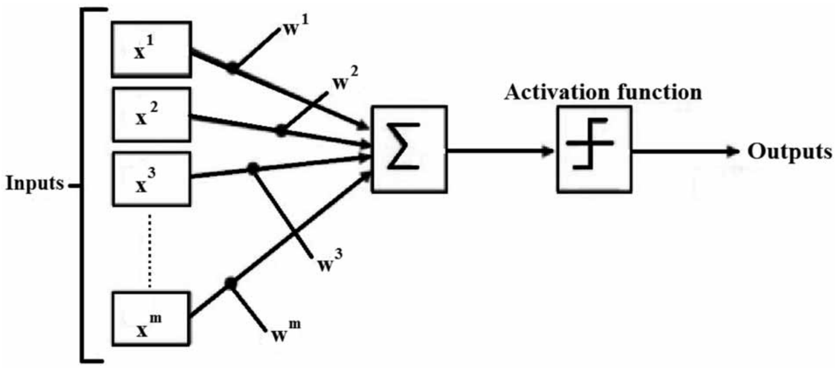

Figure 1 | ANN model layers.

requires a trial-and-error process to evaluate the appropriate combinations of input variables and data allocation for training, testing, and validation of the model. Calibration of the model, also known as training, is conducted by applying adjustments within the ANN model weights/links in order to reduce the error in the network outputs. Through this training process, a learning system is developed that is capable of determining the relation between rainfall, temperature, and flow data. Thus, validation of ANN models is focused on evaluating the trained model, which can then be used to determine flow to the reservoir under specific, hypothesized climate/weather conditions.

One of the most widely used methods in time series forecasting is the classical multi-layer perceptron network (MLP) with the back-propagation (BP) learning algorithm (Bishop 2000). Often, the MLP model is also combined with statistical models in hybrid systems (Tseng *et al.* 2002). The MLP model is one of the basic models but often produces very good results. The algorithm is based on minimizing the error of neural network output compared to targets. To maintain mathematical rigor, the weights will be adjusted only after all the test vectors are applied to the network. Therefore, the gradients of the weights must be memorized and adjusted after each model in the training set, and the end of an epoch of training, and the weights will be changed only once, because the idea is to find the minimum error function in relation to the connection's weights. In a local minimum, the gradients of the error become zero and the learning no longer continues. A solution is multiple independent trials, with weights initialized differently at the beginning, which raises the probability of finding the global minimum. For large problems, this thing can be hard to achieve and then local minimums may be accepted, with the condition that the errors are small enough. Also, different configurations of the network might be tried, with a larger number of neurons in the hidden layer or with more hidden layers, which, in general, lead to smaller local minimums. Still, although local minimums are indeed a problem, practically they are not unsolvable. An important issue is the choice of the best configuration for the network in terms of the number of neurons in hidden layers. In most situations, a single hidden layer is sufficient. There are no precise rules for choosing the number of neurons. In general, the network can be seen as a system in which the number of test vectors multiplied by the number of outputs is the number of equations and the number of weights represents the number of unknowns. The equations are generally non-linear and very complex and so it is very difficult to solve them precisely through conventional means. Choosing the activation function for the output layer of the network depends on the nature of the problem to be solved. For the hidden layers of neurons, sigmoid functions are preferred, because they have the advantages of being both non-linear and differential. The biggest influence of a sigmoid on the performances of the algorithm seems to be the symmetry of origin.

The Levenberg–Marquardt method is one of the fastest learning algorithm methods for MLP networks (Hagan & Menhaj 1994; Lourakis 2005; Sotirov 2005). The Levenberg–Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions (Sotirov 2005). It has become a standard technique for non-linear least-squares problems (Lourakis

2005), widely adopted in a broad spectrum of disciplines. LM can be thought of as a combination of steepest descent and the Gauss–Newton method.

As noted above, the LM algorithm is a variant of the Gauss–Newton method and was designed to approach second-order training speed without having to compute the Hessian matrix (Hagan & Menhaj 1994). Typically, for the learning of feed-forward neural networks, a sum of squares is used as the performance function.

Simulated precipitation outputs from global climate models (GCMs) can exhibit large systematic biases relative to observational datasets (Mearns *et al.* 2012; Sillmann *et al.* 2013). As GCM precipitation series are used as inputs to process models (e.g., Hagemann *et al.* 2011; Muerth *et al.* 2013) and gridded statistical downscaling models (e.g., Wood *et al.* 2004; Maurer & Hidalgo 2008; Maurer *et al.* 2010), algorithms have been developed to correct and minimize these biases as sources of error in subsequent modeling chains. Systematic errors in climate model outputs can be ascribed to different sources. For example, Eden *et al.* (2012) classify errors in GCM precipitation fields as being due to: (1) unrealistic large-scale variability or response to climate forcing, (2) unpredictable internal variability that differs from observations (e.g., as might happen if the sampled historical period happens to coincide with the positive phase of the Pacific decadal oscillation in observations and the negative phase in the climate model), and (3) errors in convective parameterizations and unresolved subgrid-scale orography. Quantile mapping is often applied for two very different reasons: (1) as a bias correction applied to climate model and observed fields at similar scales and (2) for downscaling from coarse climate model scales to finer observed scales. In this study, quantile is applied as the bias correction step of a larger downscaling framework. The QM for precipitation preserves model-projected relative changes in quantiles, while at the same time correcting systematic biases in quantiles of a modeled series with respect to observed values.

Quantile mapping

Quantile mapping equates cumulative distribution functions (CDFs) $F_{o,h}$ and $F_{m,h}$ of, respectively, observed data $x_{o,h}$, denoted by the subscript o, and modeled data $x_{m,h}$, denoted by the subscript m, in a historical period, denoted by the subscript h. This leads to the following transfer function:

$$\hat{x}_{m.p}(t) = F^{-1}_{o.h}\{F_{m.h}[x_{m.p}(t)]\} \quad (1)$$

for bias correction of $x_{m,p}(t)$, a modeled value at time t within some projected period, denoted by the subscript p. If CDFs and inverse CDFs (i.e., quantile functions) are estimated empirically from the data, the algorithm can be illustrated with the aid of a quantile–quantile plot, which is the scatterplot between empirical quantiles of observed and modeled data (i.e., the sorted values in each sample when the number of observed and modeled samples are the same). In this case, QM amounts to a lookup table whose entries are found by interpolating between points in the quantile–quantile plot of the historical data. The transfer function is constructed using information from the historical period exclusively; information provided by the future model projections is ignored. QM, like all statistical postprocessing algorithms, relies strongly on an assumption that the climate model biases to be corrected are stationary (i.e., that characteristics in the historical period will persist into the future). As it is beyond the scope of this paper to address this assumption, we instead point to studies by Maraun *et al.* (2010) and Maraun (2012) for more insight. For empirical CDFs, Equation (1) is only defined over the historical range of the modeled dataset. If a projected value falls outside the historical range, then some form of extrapolation is required, for example using parametric distributions following Wood *et al.* (2004) or the constant correction approach of Boé *et al.* (2007). Regardless, one way in which frequent extrapolation can be avoided is to explicitly account for changes in the projected values, for example, by first removing the modeled trend in the long-term mean prior to QM, which will shift the future distribution so that it tends to lie within the support of the historical distribution, and then reimpose it afterwards. For a ratio variable like precipitation, trends are removed and then reimposed by scaling and rescaling:

$$\hat{x}_{m.p}(t) = F^{-1}_{o.h}\left\{F_{m.h}\left[\frac{\bar{x}_{m.h}x_{m.p}(t)}{\bar{x}_{m.p}(t)}\right]\right\}\frac{\bar{x}_{m.p}(t)}{\bar{x}_{m.h}} \quad (2)$$

where $x_{m,h}$ and $x_{m,p}(t)$ are, respectively, estimates of the long-term modeled mean over the historical period and at time t in the projected period p.

Bargaining game

There is a high risk of water conflicts in the allocation of water resources in international basins. Cooperative negotiations among countries are often required to solve the water resources sharing problems in these basins (Kampragou et al. 2007), which can produce greater economic, ecological, and political utility and make sure the allocation is fair and stable (Sadoff & Grey 2002). One of the theoretical games which simulates these negotiations and cooperation is the asymmetric bargaining game (Houba et al. 2013). This bargaining solution is based on the Nash bargaining equilibrium solution (Nash 1950). The bargaining problem can be represented as $B{:}(S, D, u_1, u_2, \ldots, u_n)$ where S is the feasibility space, $\{u_i(S), i = 1, 2, \ldots, n\}$ is the utility function of the claimant, $D = d_1, d_2, d_3, \ldots, d_n$ is disagreement point, and $u_i{:}S \rightarrow R$ is the feasible solution. For any strategy selection $s \epsilon S$ the allocations should satisfy $u_i(d_i) \leq u_i(S)$. The utility configuration set of the bargaining problem can be expressed as $\{u_i(S), \ i = 1, \ 2 \ldots, n\}$. Assuming the bargaining weight of each subject: $W = (w_1, w_2, \ldots, w_n)$, $\sum_{i=1}^{n} w_i = 1$. The only solution that satisfies the following maximization condition is the Nash bargaining solution:

$$u^N(s) = \{s \epsilon S | max[(u_1(s) - u_1(d_1))^{w_1} (u_2(s) - u_2(d_2))^{w_2} \ldots (u_n(s) - u_n(d_n))^{w_n}]\} \tag{3}$$

Bargaining power calculation

Each player's weight will be obtained by the AHP method, which was first proposed by Saaty in 1971. It is one of the methods used for solving multi-criteria decision-making (MCDM) problems in political, economic, social, and management sciences (Saaty 1980). Through AHP, opinions and evaluations of decision-makers can be integrated, and a complex problem can be devised into a simple hierarchy system with higher levels to lower ones (Lee et al. 2009). Then, the qualitative and quantitative factors can be evaluated in a systematic manner. The application of AHP to a complex problem involves six essential steps (Murtaza 2003; Lee et al. 2006):

- Defining the unstructured problem and stating the objectives and outcomes clearly.
- Decomposing the complex problem into a hierarchical structure with decision elements (criteria and alternatives).
- Employing pairwise comparisons among decision elements and forming comparison matrices.
- Using the eigenvalue method to estimate the relative weights of decision elements.
- Checking the consistency property of matrices to ensure that the judgments of decision-makers are consistent.
- Aggregating the relative weights of decision elements to obtain an overall rating for the alternatives.

The weights gained by AHP will be implemented as subjective weights in the entropy method. This measure of uncertainty is given by Shannon & Weaver (1947) as:

$$E = P \begin{pmatrix} P_1 \\ P_2 \\ \vdots \\ P_m \end{pmatrix}, \sum_{i=1}^{m} P_i = 1 \tag{4}$$

The entropy of the set of project outcomes of attribute j is

$$E_j = -K \sum_{i=1}^{m} [P_i \cdot \ln P_i] \tag{5}$$

in which, E_j is the entropy of attribute j, m is the number of alternatives, P_i is the probability of the i-th alternative that is preferred by the decision-maker. Where k is a constant defined as

$$K = \frac{1}{\ln m} \tag{6}$$

it guarantees that $0 \leq E_j \leq 1$.

The degree of diversification of information provided by the outcomes of attribute j can be defined as:

$$d_j = 1 - E_j \ , \ j = 1, 2, \ \ldots, n \tag{7}$$

then the weights of attributes can be obtained by

$$W_j = \frac{d_j}{\sum_{i=1}^{m} d_j}\ ,\ j = 1,\ 2\ldots, n \tag{8}$$

Then the mean value of weights that is the outcome from each matrix is considered as the weights of each attribute.

For a better understanding of this research's steps and progress, a flowchart is presented in the Appendix, Figure A1.

CASE STUDY

In this study, the drainage basin of Zarinehrood was chosen to evaluate the function of selective methods. The drainage basin of Zarinehrood, with an area of 1,100 square kilometers, is the largest sub-basin of Urmia which is located in the north-west of Iran, and a valuable water resource that supplies water needs such as drinking, industrial, agricultural, and environmental, and makes 40% inflow to Urmia Lake.

Five synoptic stations were chosen to cover the whole basin which had observation data of more than 30 years, also the observation data of these stations were driven by the Water Resources Department from 1985 to 2017. In this study, for assessing climate change impact on hydrological parameters of the basin, scenarios of the Fifth IPCC reports, e.g., RCP2.6, RCP4.5, RCP6.0, and RCP8.5, were used. Historical and RCP data for precipitation, maximum and minimum temperature were downloaded from https://pcmdi.llnl.gov/mips/cmip5 in NetCDF format. The information related to the study area was extracted, comparing and using evaluation indexes in the differences of three CMIP5 models' historical data with observation data of the area, and GFDL-CM3 was chosen to be used. For downscaling outputs of GCMs, a perceptron neural network (PNN) with three layers was developed, in which for training, a Levenberg–Marquardt algorithm and a sigmoid activation function were used. For training the algorithm, historical and observation data from 1985 to 2017 in all three parameters were used, for choosing the appropriate PNN layers and dots, three evaluation methods were used, and future data from 2018 to 2050 predicted in the following steps. Because raw data reduces the speed and accuracy of PNN, at first, inputs were standardized by the following formula:

$$X_n = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{9}$$

where X_n is standardized parameter, and i, min and max, respectively, are row, minimum, and maximum of the parameter in the series.

After downscaling, a QM method for bias correction was used. In this step, difference in quantiles of observation and simulated historical data in the form of polynomial function was applied on downscaled RCP data to minimize the overall errors. In order to distribute the individual station's parameters to the whole basin, the Thiesson polygon method was used; in this method every station is in the middle of a polygon that overall covered the basin, and parameters were calculated by the following formula

$$\bar{P} = \frac{A_1P_1 + A_2P_2 + \ldots + A_nP_n}{A_1 + A_2 + \ldots + A_n} \tag{10}$$

where $A_1, A_2, \ldots, A_n$ are polygon area and $P_1, P_2, \ldots, P_n$ are parameters related to the central station.

Then, a rainfall-runoff model based on SCS method and using precipitation of climate change scenarios was developed. Next, using time series and historical data an *ARMA(p,q)* model for forecasting evaporation was created. Then, considering some assumptions for predicting future demands and using SOP (standard operating policy) method for reservoirs in the area, a water resources management program was developed to assess the water available for allocating to users. The water allocation among users is based on meeting the drinking, environmental, and industrial demand and the remainder for agriculture demand.

For allocation of available water among users, game theory concepts regarding consideration of their interactions is used. The set of players for the game consisted of West Azarbaijan, East Azarbaijan, Kordestan and because of the sensitive situation of Urmia Lake it has been considered as the fourth player of the game. A bargaining game with the NBS in two ways, one symmetric and two using the AHP method, was created. In this game, optimization game terms are as follows:

$$[f(Q_{WA}) - f(d_{WA})]^{w_{WA}}\ [f(Q_{EA}) - f(d_{EA})]^{w_{EA}}\ [f(Q_{KRD}) - f(d_{KRD})]^{w_{KRD}}\ [f(Q_{URL}) - f(d_{URL})]^{w_{URL}} \tag{11}$$

s.t:

$$Q_{WE} + Q_{EA} + Q_{KRD} + Q_{URL} \leq R_t \tag{12}$$

$$(D_{min})_{WA} \leq Q_{WA} \leq D_{WA} \tag{13}$$

$$(D_{min})_{EA} \leq Q_{EA} \leq D_{EA} \tag{14}$$

$$(D_{min})_{KRD} \leq Q_{KRD} \leq D_{KRD} \tag{15}$$

$$(D_{min})_{URL} \leq Q_{URL} \leq D_{URL} \tag{16}$$

$$w_{WA} + w_{EA} + w_{KRD} + w_{URL} = 1 \tag{17}$$

$$D_{min} = D_{dr} \tag{18}$$

where *WA*, *EA*, *KRD*, and *URL* indices are, respectively, West Azarbaijan, East Azarbaijan, and Kordestan as players, f is utility function, w is weight of each player, R_t is available water in each period of time, D is demand of each player, D_{min} and D_{dr} are minimum and drinking demand.

The bargaining weights of players were determined by AHP method and Shannon entropy. First, considering each demand of every player, an effective factor was calculated for each of the demands. Then, according to the effective factors, an overall importance weight for each player was determined and used to apply to NBS optimization.

RESULTS AND DISCUSSION

In this paper, a water allocation considering the impacts of climate change was studied.

Based on the Fifth IPCC report, an ANN model for downscaling and a QM model for bias correction impacts of climate change on Zarinehrood basin for precipitation, minimum and maximum temperature in a period of 33 years, were predicted. An output example of the process of QM correction, presented in Figure 2, shows that the accuracy percentage trend of simulated data gets closer to observation data.

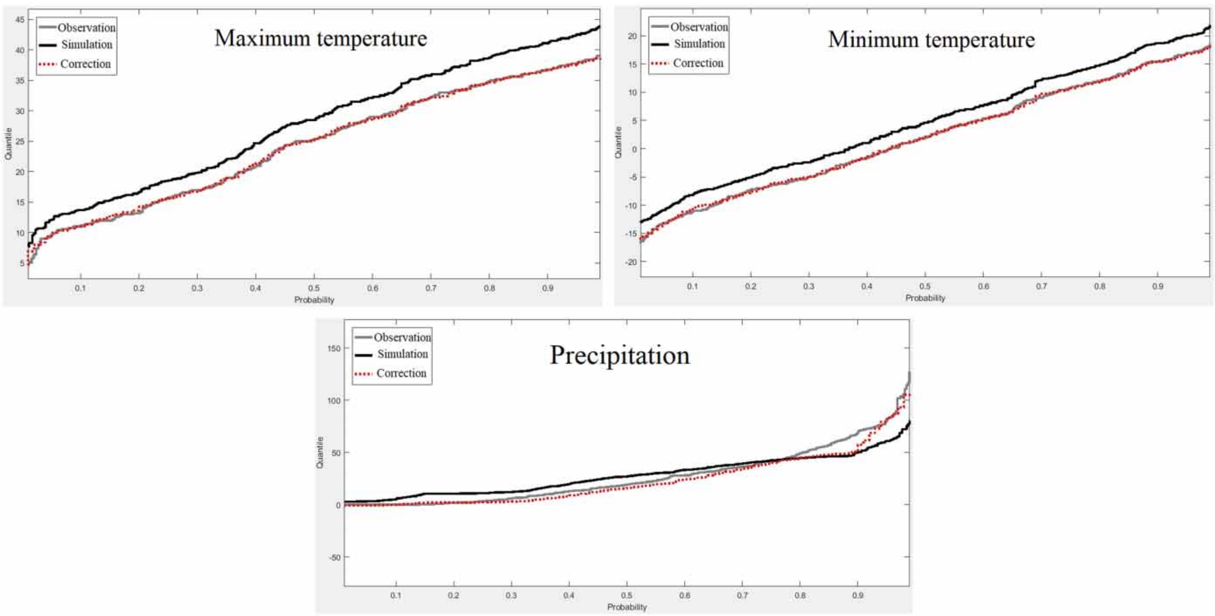

Figure 2 | Quantile mapping correction.

As for downscaling, three evaluation methods, agreement index (*AI*), root mean square error (*RMSE*), and Pearson correlation coefficient (*r*) were used, with results for five synoptic stations presented in Table 1. Correlation between observation and simulated data is between 0.6 and 0.8, which shows that in this interval the algorithm simulated data in a linear way and the reset of simulation is non-linear. The AI index is approximately near 1 which shows an acceptable connection between sets of data.

After correction of each station, distribution to the whole basin was projected and the final results of each parameter calculated for each scenario. Overall results show a decrease in both minimum and maximum temperatures, in which, from RCP2.6, to RCP4.5, to RCP6.0, and to RCP8.5 rises are greater, with RCP8.5 having a peak of almost +3.6 °C. As for precipitation, there are rises at peak daily rainfall, but the overall monthly precipitation has a negative trend, in which from RCP2.6, to RCP4.5, to RCP6.0, and to RCP8.5 decreases in rainfall are greater. For example, better comparison results for one of the stations, i.e., Mahabad, are presented in Figure 3. For this station an average yearly observation precipitation was 395 mm, and the values for RCPs from RCP2.6, to RCP4.5, to RCP6.0, and to RCP8.5 are around 390, 365, 345, and 335 mm. Two scenarios, RCP2.6 and RCP8.5, are chosen for the next step in allocation.

Using an *ARMA(10,1)* model for evaporation estimation, the SOP method for reservoir's release and SCS method for rainfall-runoff, water available for allocation was determined. The results show a positive trend at the end of the prediction interval for RCP2.6 and a negative one for RCP8.5.

Calculating bargaining weights using Shannon entropy, E index for each player dividing by demands, and E_j, d_j, and W_j for each demand, are presented in Tables 2 and 3.

Based on the results of each demand's weights from Shannon entropy, the bargaining power of players' set: *{WA, EA, KRD, URL}* are, respectively, {0.425, 0.234, 0.06, 0.281}. These powers show that sensitivity and importance among players (from the first to the last) are players *WA*, *URL*, *EA*, and *KRD*.

Using symmetric NBS and asymmetric NBS based on the AHP method, the results of players' utility function are represented in Table 4.

Table 4 shows that with a symmetric assumption for bargaining, utilities are not the same and the player with the largest demand has the highest utility and the same goes for the lowest demand and utility; but, asymmetric powers which are determined by AHP provide almost the same utility for all players which means higher satisfaction and lower chance of leaving the agreement in the players' set. For a fair and stable game set, bargaining power based on the demands of each player and each demand's priority should be considered.

CONCLUSION

In this study, water allocation under the effects of climate change based on game theory was implemented for the Zarinehrood River basin located in the north-west part of Iran. The main objective is to work and evaluate selected methods for achieving this goal.

For the first phase of the study, which is assessing climate change impacts, models were developed on the

Table 1 | ANN evaluation index

	Maximum temperature			Minimum temperature			Precipitation		
Station	**RMSE**	**r**	**AI**	**RMSE**	**r**	**AI**	**RMSE**	**r**	**AI**
Takab	0.001	0.788	0.9063	0.001	0.745	0.9130	0.003	0.755	0.9425
Mahabad	0.005	0.679	0.9112	0.004	0.684	0.9215	0.004	0.678	0.9544
Zarineh	0.004	0.682	0.9532	0.005	0.649	0.9461	0.001	0.622	0.9167
Maragheh	0.004	0.780	0.9074	0.003	0.753	0.9713	0.003	0.798	0.9538
Saghez	0.002	0.752	0.9637	0.006	0.632	0.9889	0.002	0.695	0.9442

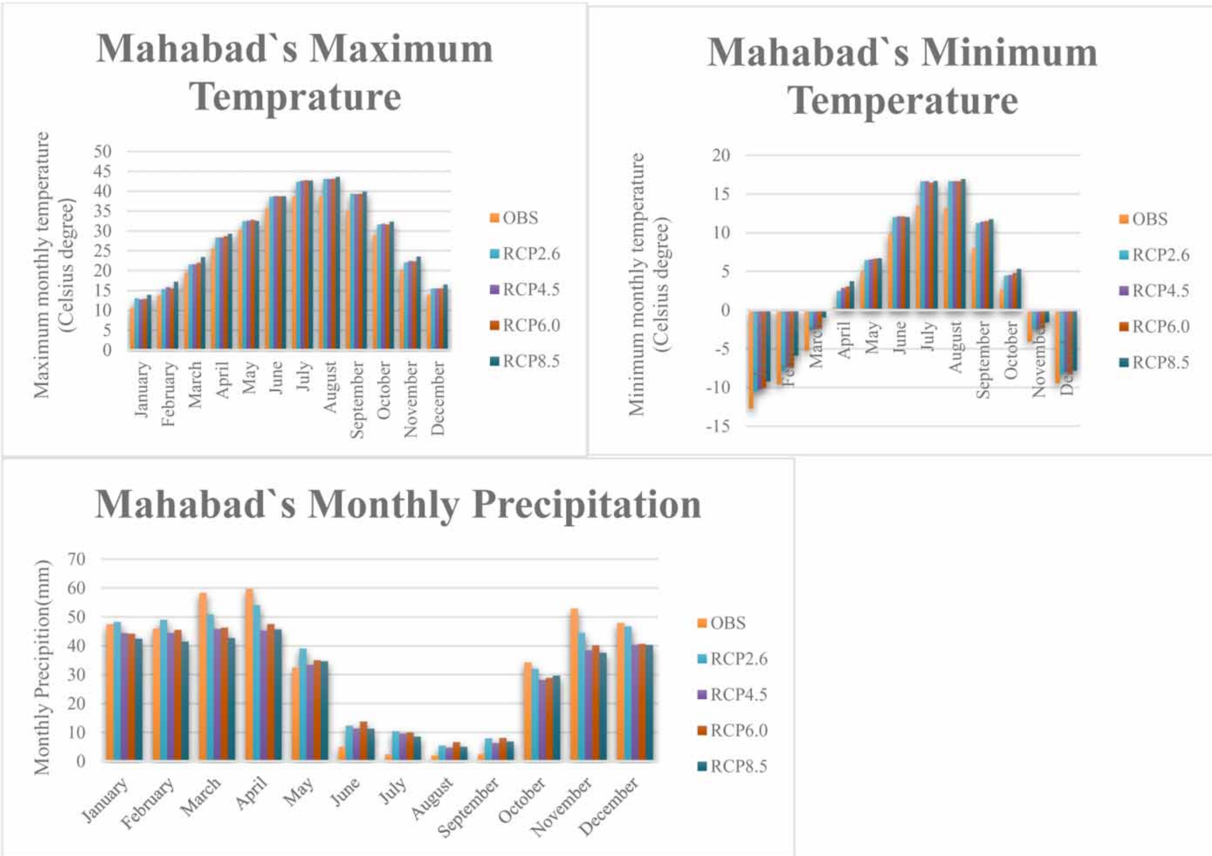

Figure 3 | Precipitation, maximum and minimum temperatures.

Table 2 | E index

Players	Environmental	Agricultural	Industrial	Drinking
WA	0.322904	0.309192	0.366285	0.32762
EA	0.283974	0.365298	0.360781	0.36733
KRD	0.233706	0.202665	0.288856	0.366341
URL	0.355355	–	–	–

Table 3 | Ej, dj, and Wj for each demand

Index	Environmental	Agricultural	Industrial	Drinking
E_j	0.862688	0.632734	0.732833	0.765561
d_j	0.137312	0.367266	0.267167	0.234439
W_j	0.1365	0.3650	0.2655	0.2329

future runoff from three factors, minimum and maximum temperature and rainfall, using the Fifth IPCC report. The results with three evaluation indices showed that ANN

Table 4 | Players' utility

	2.6		8.5	
Player	AHP	Symmetric	AHP	Symmetric
WA	60.39	56.06	50.25	43.84
EA	63.98	60.14	52.95	57.35
KRD	65.6	88.08	59.94	83.49
URL	63.25	64.55	57.22	56.45

models for downscaling together with the QM model for bias correction can be used as a predictive algorithm that provides a good predictive accuracy. Testing of the trained ANN produced a similarly good fit. In general, the use of these two methods together can give a good confidence quantity limit.

Considering the complexity and systemics of water resources allocation to establish a bargaining power evaluation index system of countries in the negotiations and use in the bargaining game of water resources distribution make the bargaining game model more reasonable and realistic (Svejnar 1986). Hence, this work has made efforts to find water allocation methods that are fair, efficient, and sustainable. When the minimum survival water demand is considered, the disagreement points are more reasonable than when the minimum survival water demand is not considered. This method could avoid the unreasonable phenomenon in which there are disagreement points below the minimum water supply, or zero. The proposed disagreement points can guarantee basic water demands are met. In the process of water resources allocation, calculation of the bargaining weights using the AHP method can result in an efficient, equitable, and sustainable benefit among stakeholders, which could be more in line with actual water resources allocation. The results can be utilized as a basis for supporting decision-makers of a river basin to resolve social conflicts.

Regarding Zarinehrood basin, results show an increase in peak daily rainfall but reduction in overall precipitation which follows water deficiency. Also, an increase in temperature results in evaporation growth and this too follows with a reduction in available water. Allocation using bargaining power driven by the AHP method showed an equity in participants' utility which follows satisfaction of parties and a more stable union with a minimum chance of leaving the agreement.

In general, considering climate change's three parameters, the demands of each player, each demand's priority, and the lowest point of demand, and also taking into account Urmia Lake as a player due to its critical situation, this water allocation prediction was good and fair.

For improvement of this study, using a different rainfall-runoff model, multi-model climate change methods, and another assumption on demands are recommended.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this paper is available online at https://dx.doi.org/10.2166/wcc.2020.153.

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