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Optimal Water Allocation of Surface and Ground Water Resources Under Climate Change with WEAP and IWOA Modeling

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Abstract

The water evaluation and planning (WEAP) approach and the invasive weed optimization algorithm (IWOA) are herein employed to determine the optimal operating policies in conjunctive (surface water/groundwater) systems for water supply in agricultural municipal/industrial (M&I) sectors under climate change. Climatic variables are simulated with atmospheric-ocean general circulation models (AOGCMs) under emission scenarios A2 and B2 during the baseline period 1971–2000 and the future periods 2040–2069 and 2070–2099 in the Khorramabad basin, Iran. The Hadley Centre Coupled Model, version 3 (HadCM3), and the Canadian Global Coupled Model, version 2 (CGCM2), produced superior temperature and rainfall projections, respectively, than other climate models. Under both emissions scenarios and during each future period, this study indicates an increase in temperature and a decrease in rainfall. Simulations of surface water with the IHACRES (Identification of unit Hydrographs And Component flows from Rainfall, Evaporation and Streamflow data) calibrated model shows a decrease in the future runoff. The Groundwater Modeling System (GMS) calibrated software projects a decrease in water level and a decrease in recharge under climate change scenarios. Simulation results from IHACRES and GMS are input to the Water Evaluation and Planning (WEAP) system to develop operational policies for the combined use of water resources., The water-allocation reliability of the system is estimated with the WEAP system for 24 scenarios reflecting climate change scenarios assuming increases in water demand, ranging from 10 to 60% in agriculture and from 20 to 30% in the municipal and industrial (M&I) sector. The IWOA is applied to optimize the conjunctive system of water resources (i.e., surface water and groundwater). The objective function is to maximize the system's water allocation reliability. The range of optimal water-allocation reliability changes is between 3 and 16%, with the lowest increase corresponding to the baseline period for agricultural water demand, and the highest rise corresponding to an increase of 50% in water demand under the B2 emissions scenario in 2040–2069 for the M&I water sector.

Keywords Climate change · Optimal operating of surface water and groundwater conjunctive systems · Invasive weed optimization algorithm

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1 Introduction

The rise of economic activity concomitant with population growth, plus the exacerbation of climatic change impacts, has increased water scarcity in many parts of the world. Climate-change impacts are clearly seen in evolving patterns of surface temperature and precipitation (Intergovernmental Panel for Climate Change, IPCC 2007). The development and application of simulation–optimization methods (SOMs) has been proven an effective approach for identifying adaptation strategies to the changing availability of water resources in growing economies (Azadi et al. 2021). Various studies concerning SOMs for water resources management have appeared in the literature. A selected few are herein reviewed.

Mehrabian and Lucas (2006) introduced the invasive weed optimization (IWO) algorithm for solving a set of benchmark multi-dimensional functions. The results were compared with other recent evolutionary-based algorithms: genetic algorithms (GAs), memetic algorithms, particle swarm optimization (PSO), shuffled frog leaping (SFL) optimization, versions of simulated annealing, and direct search simulated annealing. The performance of IWO was superior with respect to all the test functions compared with those of the other comparison methods. Yang et al. (2009) proposed an approach for integrating the multi-objective genetic algorithm (MOGA), constrained differential dynamic programming (CDDP), and the groundwater simulation model ISOQUAD. A MOGA was used to generate the various fixed costs of reservoirs. The ISOQUAD was embedded to handle the complex dynamic relationship between the groundwater level and the generated pumping/recharge pattern. The CDDP was applied to distribute the optimal releases among reservoirs. Lastly, the effectiveness of an integrated model was verified for the conjunctive use of surface and subsurface water in southern Taiwan. Tabari and Soltani (2013) developed a multi-objective model to maximize the minimum reliabilities of a water system and minimize costs. The non-dominated sorting genetic algorithm (NSGA-II) was implemented to present the optimal trade-off between the objectives. The sequential genetic algorithm (SGA) was compared with the NSGA-II. The results showed that the NSGA-II could reduce the computational burden of the conjunctive use models in comparison with the SGA. Wu and Chau (2013) employed several soft computing approaches for rainfall prediction. Results showed that the artificial neural network (ANN)-moving average (MA) (ANN-MA) displayed considerable accuracy in rainfall forecasts compared with the benchmark. Taormina and Chau (2015) applied the Lower Upper Bound Estimation (LUBE) to build streamflow prediction intervals. LUBE method enhanced via Multi-Objective Fully Informed Particle Swarm (MOFIPS). Wu et al. (2016) implemented physically-based, fully integrated surface water and groundwater (SW-GW) modeling in optimizing water management, and performed surrogate modeling to replace the computationally expensive model with simple response surfaces. Water-use conflicts between agriculture and ecosystem in Heihe River Basin (HRB), in China, were investigated. Safavi and Enteshari (2016) presented a simulation/optimization model based on artificial neural networks (ANNs) and ant system (AS) optimization for solving the monthly conjunctive supply of irrigation water in the Najafabad Plain located in Iran. The main objective was to minimize the water deficit in the three irrigation zones subject to constraints on groundwater levels and cumulative drawdown for each zone. Asgari et al. (2016) introduced the weed optimization algorithm (WOA) to optimal reservoir operation. The WOA was applied in continuous-time and discrete-time formulations of reservoir-operation optimization, and its results were compared with global optimal solutions obtained with nonlinear programming (NLP), linear programming (LP), and the GA. The results indicated the WOA's fast convergence. Zheng et al. (2017) recommended the use of run-time measure metrics to reveal the underlying searching behavior of multi-objective evolutionary algorithms (MOEAs) operators. The proposed methodology was illustrated with the non-dominated sorting genetic algorithm (NSGA-II) with five crossover operators applied to six water distribution system design problems. Moutsopoulos et al. (2017) used the Visual MODFLOW software to simulate groundwater flow, while the GA and the Tabu Search Algorithm were employed to maximize the extracted flow rates and investigate the optimal groundwater management strategy of an unconfined aquifer. Mousavi et al. (2017) presented a simulation–optimization (SO) framework for reliability-based optimal sizing, operation, and water allocation in the Bashar-to-Zohreh inter-basin water transfer project in Iran. The problem was formulated as a mixed integer nonlinear program (MINLP). The SO framework linked the WEAP system to the multi-objective particle swarm optimization (MOPSO) for multi-period optimization. The objective functions minimized the sizes of the project's infrastructures and maximizing the reliability of supplying water to agricultural lands. Azari et al. (2018) developed the WEAP-NSGA-II coupling model to apply the hedging policy to a water resources system in Iran. Periods of water shortage were simulated for the next 20 years by defining a reference scenario and applying the operation policy based on the current situation. Sepahvand et al. (2019) applied a simulation–optimization model to perform conjunctive management of surface-ground water use to achieve: (1) minimizing shortages in meeting irrigation water demands and (2) maximizing the total agricultural net benefit for the main crops of an agricultural sector. The genetic programming (GP) method used to simulate surface water-groundwater interactions. Next, the simulation model was linked to a multi-objective genetic algorithm (MOGA) as the optimization model, yielding a simulation–optimization model. Golfam et al. (2019) evaluated the VIKOR and FOWA multi-criteria decision-making methods for adaptation with climate change of Agricultural Water Supply. Climate-change projections were made for the period 2040–2069. Cropping patterns were assessed using the WEAP system leading to the calculation of decision-making indexes. Alamanos et al. (2020) examined a common hydro-economic framework for sustainable water resources management. They developed two Hydro-Economic Models (HEMs) to address challenges regarding data limitations, spatial analysis, and scenario-based problems. Li et al. (2020) presented a Multi-objective Uncertain Chance-Constrained Programming (MUCCP) approach between multi-water resources and multiple water users. MUCCP model set the economic, social and environmental benefits as objectives with capacities of water supply and demand as uncertain chance constraints. van der Voorn et al. (2020) assessed the potential conflicts and synergies between multiple environmental policy goals based on four future scenarios on Swedish rural land use, assuming zero GHG emissions in 2060. Four future scenarios which include many goals were (1) Centralized governance Biomass Focus, (2) Centralized governance Electricity Focus, (3) Localized governance Biomass Focus, (4) Localized governance Electricity focus. The choice of strategy to meet a goal can resolve conflicts or create synergies. Golfam et al. (2021) modeled the adaptation policies to increase the synergies of water-climate-agriculture nexus under climate change. Majedi et al. (2021) developed a multi-objective optimization model of integrated surface and groundwater resources. The aquifer water balance and surface water resources were simulated with the MODFLOW model and WEAP, respectively. The objective functions were the maximization of supply of demands and hydropower and the minimization of aquifer drawdown. They applied the NSGA-II for this purpose. Chen et al. (2021) reported a flood control operation model with minimum flood volume stored in each reservoir and minimum peak flow at downstream control points during the dispatch process. They developed a flood forecast model by coupling the Yin-Yang firefly algorithm (YYFA) with the ε constrained method. Wang et al. (2021) presented a novel prediction model for annual runoff based on sample entropy, secondary decomposition, and long short-term memory neural network. Xie et al. (2022) focused on two types of Machine learning-based algorithms for modeling Green Roofs (GRs) hydrological performance. Results showed that both models were useful tools for GR modelling.

Iran's geography features mostly dry and semi-arid climate regions, and is particularly vulnerable to the phenomenon of climate change. Several studies have been carried out on simulation–optimization of conjunctive water resources systems (i.e., linked surface water-groundwater resources); yet; the effect of climate change has not been considered in previous studies of conjunctive use of water resources. This paper develops the optimal operation of conjunctive systems (surface water and groundwater) under climate change conditions using the invasive weed algorithm (IWOA). This paper's results will be useful to those seeking to optimize withdrawals from surface and groundwater taking into account future conditions. For this purpose, firstly, the climatic data for the baseline period of 1971–2000 and the future periods 2040–2069 and 2070–2099 are extracted from the output of several AOGCMs, and the corresponding time series are simulated. Subsequently, the surface water resources of the Khorramabad Basin, Iran, are simulated with the IHACRES calibrated model under two emission scenarios A2 and B2 in the two future periods. Groundwater simulation is then performed with the calibrated GMS software to project groundwater fluctuations. The WEAP approach is implemented to simulate the status of surface and groundwater resources, from which the monthly water allocations for the M&I and agricultural sectors are determined. Lastly, the IWOA is implemented to optimize (i) the conjunctive use of water resources to meet water demands (this is the key innovation in this research), (ii) the water resources system's water allocation reliability under different scenarios, and (iii) the water allocations for the agricultural and the M&I sectors.

2 Methodology

Climatic pre-processing is performed based on AOGCMs projections under emission scenarios, hydrological simulations are obtained with the IHACRES and GCM models, and water resources interactions (including surface water and groundwater) and water use are simultaneously simulated and evaluated under climate change scenarios. Lastly, the reliability of the conjunctive water-resources system is optimized using the IWOA algorithm. An outline of the paper's methodology is depicted in Fig. 1.

2.1 Simulation

Section (a) presents the climatic scenarios and climate projections; Section (b) outlines the simulation of surface flow, groundwater flow, and the optimization of conjunctive water resources.

a) Climatic scenarios

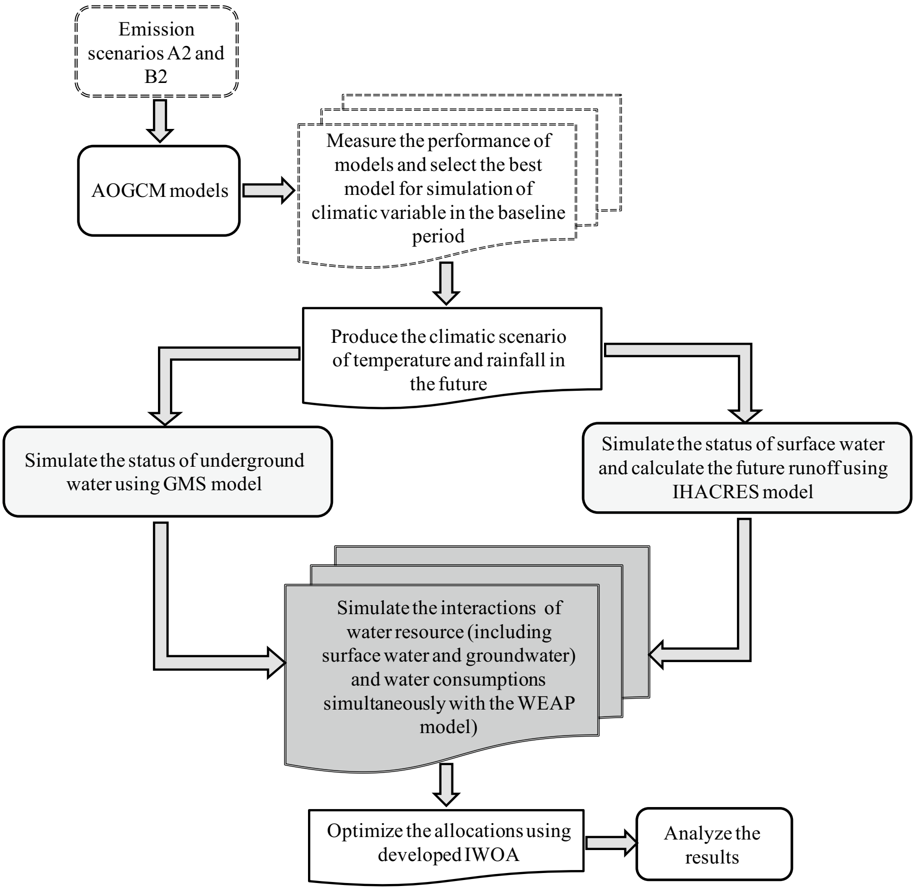


Fig. 1 Flowchart of this research

Greenhouse gases emission scenarios presented in the Third Assessment Report (TAR) and the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) are used to make climate projections for the twenty-first century. Emissions scenario A2 assumes the largest CO2 emissions among all emission scenarios; Scenario B2 appears to be the most representative of future economic condition of Iran. The emission scenarios A2 and B2 represent worst-case and most likely scenarios, respectively, are employed in this study. Long-term averaging of the AOGCMs' climate predictions are herein used to smooth out inter-model variations. The change-factor method is applied for downscaling the data in this work (Lane et al. 1999; Mitchell 2003; Wilby and Harris 2006; IPCC-TGCIA 1999; IPCC 2007; Jones and Hulme 1996). This method first calculates the values of temperature difference and rainfall ratio of simulated long-term monthly temperature and rainfall in the future and the baseline periods in each cell of the computational network of AOGCMs [Eqs. (1)-(2)]. The difference values are added to the observed values of temperature, and the ratio values are multiplied by the observed value of rainfall [Eqs. (3)-(4)] (Wilby and Harris 2006).

$$\Delta X_i = \overline{X}_{AOGCM,fut_i} - \overline{X}_{AOGCM,bas_i} \tag{1}$$

$$\Delta Y_i = \overline{Y}_{AOGCM,fut_i} / \overline{Y}_{AOGCM,bas_i} \tag{2}$$

$$X_t = X_{obs} + \Delta X_i \tag{3}$$

$$Y_t = Y_{obs} + \Delta Y_i \tag{4}$$

In which, ΔX_i and ΔY_i = the climate change scenario related to temperature and rainfall for the long-term average for each month, respectively ($1 \leq i \leq 12$); $\overline{X}_{AOGCM,fut_i}$ and $\overline{Y}_{AOGCM,fut_i}$ = the average temperature and rainfall simulated by AOGCM for the future period in each month, respectively; $\overline{X}_{AOGCM,bas_i}$ and $\overline{Y}_{AOGCM,bas_i}$ = the average temperature and rainfall simulated by AOGCM for the baseline period in each month, respectively; X_{obs} and Y_{obs} = the time series of observed temperature and rainfall in the baseline period; X_t and Y_t = the time series from the climate scenario of temperature and rainfall in the future periods.

b) Conjunctive use of water resources

Conjunctive use of water resources means an integrated regional management of surface water and groundwater. Conjunctive use takes many forms, such as managed aquifer recharge (MAR) whereby surface water is stored during wet periods and conveyed for recharge (primarily in spreading basins) in aquifers for use during periods of high-water use; or as aquifer storage recovery (ARS) defined as the storage of water in an aquifer through wells during times when water is available for recovery of the water during times when it is needed (Pyne 2005). Runoff (the surface water resource) is simulated in future periods with the IHACRES rainfall-runoff model (Jakeman and Hornberger 1993). The IHACRES model converts temperature and rainfall to effective rainfall and surface runoff employing nonlinear and linear modules, respectively. The GMS software coupled with the MODFLOW groundwater model are employed to simulate groundwater flow. The GMS software performs quantitative and qualitative groundwater simulations with finite difference and finite element numerical methods. The WEAP system is herein implemented for water resources assessment and to optimally allocate water resources to meet water demand. A key feature of WEAP is the integrated approach to simulating water systems for identifying water-management policies. The basis of the WEAP system is reliance on the basic equation of water balance for water system simulation. The WEAP approach is implemented to construct and evaluate water use and management scenarios. It is herein coupled with the IWOA to find optimal schemes for integrated water resources management.

2.2 Optimization

The IWOA is a randomized meta-heuristic search method in multidimensional spaces of decision variables that emulates the propagation behavior of weeds or plants. The sole goal of a weed is survival, and to achieve this goal it seeks the best environment for life support. The stages of the IWOA are as follows:

1. Production of population from initial possible solutions

A limited number of seeds are randomly distributed in multi-dimensional search space. These seeds produce plants (possible solutions) in each algorithmic iteration, and the plants' fitness is evaluated to select those who will generate new seeds leading to improved populations of plants from one iteration to the next until reaching a stopping criterion.

2. Reproduction

Each plant produces seeds based on their quality and fitness. The reproduction diagram of each plant according to fitness is shown in Fig. 2. The number of generated seeds is determined according to Eq. (5):

$$S = \left[S_{\min} + \left(S_{\max} - S_{\min}\right) \cdot \left(F - F_{worst}\right) / \left(F_{best} - F_{worst}\right)\right] \tag{5}$$

In where, S = number of seeds produced by a plant; $S_{\max}$ = the maximum number of allowed seeds produced by a plant; $S_{\min}$ = the minimum number of authorized seeds produced by a plant; F = the fitness of plant; F_{best} = the best fitness of a plant; and F_{worst} = the worst fitness of a plant.

3. Spatial dispersal

Child-plant seeds are scattered near the mother plant using a normal distribution with an average of zero and different variances in the multi-dimensional search space. The standard deviation, according to Eq. (6), decreases from the maximum value to the minimum nonlinearly. Due to this nonlinear reduction the generated seeds are initially far away from the mother plant, and with increasing number of iterations they are placed near the mother plant.

$$\sigma_t = \left(\frac{T - t}{T}\right)^n \cdot \left(\sigma_f - \sigma_l\right) + \sigma_l \tag{6}$$

In which, σ_t = standard deviation of current iteration; T = the maximum iteration; t = the number of current iteration; n = reduction speed controller; σ_f = the initial standard deviation; and σ_l = the final standard deviation.

4. Competitive exclusion stage

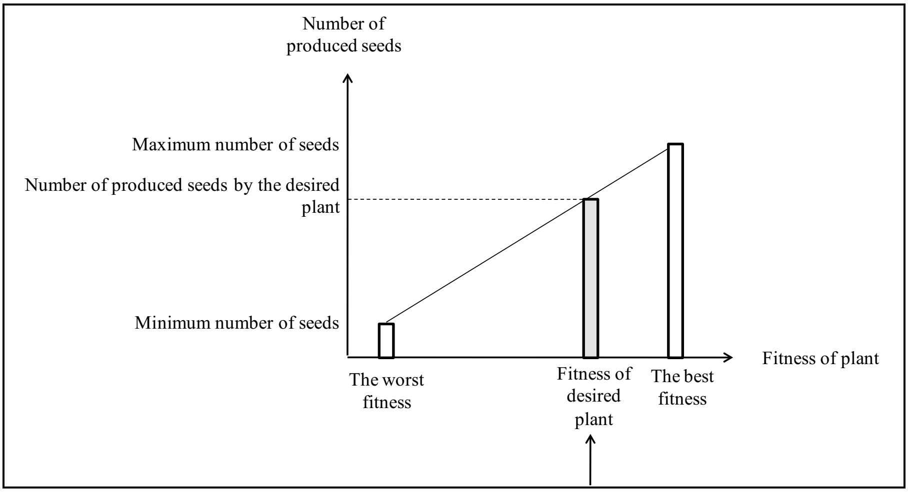


Fig. 2 The reproduction pattern of each plant according to fitness

A competitive exclusion process is performed weeds to control the maximum number of weeds. This process is such that weeds with low fitness are removed from the rest of the weeds. Weed reproduction continues to involve the fittest plants, and only plants with superior quality can survive and produce seeds.

2.3 Integration of the Simulator and Optimizer Model

The code of the IWOA algorithm was written in MATLAB including linkage to the WEAP system to create a simulation–optimization method. The objective function is to maximize the reliability of water allocations. The decision variables are water allocations to meet agricultural and M&I water demands. The water resources system is simulated with the WEAP system given a set of initial water allocations; these allocations are then evaluated for fitness with the IOWA to generate improved water allocations, which in turn are used to simulate the water resources system anew. These simulation (with WEAP) and optimization (with the IWOA) iterations are repeated until reaching a stopping milestone. The objective function is to maximize the reliability of water allocations according to Eq. (7):

$$Maximize\,OF = \sum_{t=1}^{T} \frac{COUNT\left(S_t \geq D_t\right)}{T} \tag{7}$$

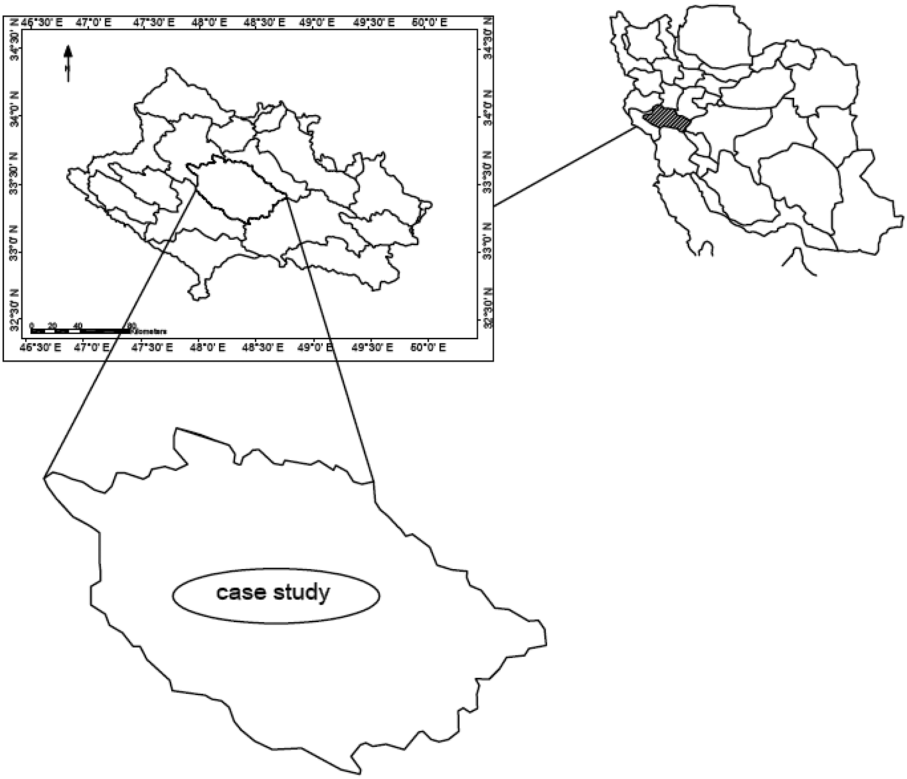


Fig. 3 Location of the study area

In where, OF = objective function (time reliability); S_t = the allocated water in month t; D_t = the water demand in month t; $COUNT$ = the count function; and T = number time intervals of water resources system's operation.

The constraints of the problem are as according to the Eqs. (8)-(9):

$$0 \leq S_t \leq D_t \tag{8}$$

$$0 \leq e_t \leq Q_t - S_t \tag{9}$$

In where, Q_t = river flow (streamflow); and e_t = the minimum environmental base flow in month t.

2.4 Geographical Location of the Studied Area

The study area is the Khorramabad river basin, which is located in Lorestan province in western Iran. Surface flow in the region is the Khorramabad River. Monthly temperature, rainfall, and streamflow data corresponding the baseline period (1971–2000) are extracted from the Cham-anjir hydrometric station. Figure 3 depicts the location of the study area.

Water resources and water use in the study area include the river-aquifer system, and agricultural and M&I water demands. The river meets the demands of agriculture only, while the aquifer meets M&I water demands and some of the agricultural water demand.

3 Results and Discussion

3.1 Climatic Scenarios

Outputs from five AOGCMs (i.e., CCSR-NIES, CGCM2, CSIRO-M2K, GFDL-R30, and HadCM3) were herein used to construct rainfall and surface temperature projections in the study area corresponding to the future periods of analysis. The coefficient of determination (R^2), root mean square error ($RMSE$), mean absolute error (MAE), and the Nash-Sutcliff efficiency (NSE) were calculated to conclude the HadCM3 and the CGCM2 models yielded the best projections for temperature and rainfall, respectively. The performance results for

Table 1 Performance of AOGCMs for surface temperature

Models	Temperature							
	A2				B2			
	R^2 (%)	*RMSE* (℃)	*MAE* (℃)	*NSE* (dimensionless)	R^2 (%)	*RMSE* (℃)	*MAE* (℃)	*NSE* (dimensionless)
HadCM3	<u>94</u>	<u>3</u>	<u>2.3</u>	<u>0.8</u>	<u>94</u>	<u>3</u>	<u>2.4</u>	<u>0.8</u>
GFDL R30	92	4.5	3.8	0.7	93	4.6	4	0.6
CGCM2	97	6.4	5.8	0.4	97	6.5	5.9	0.3
CSIRO MK2	87	4.1	3.4	0.7	87	4.1	3.3	0.7
CCSR-NIES	92	3.8	3.1	0.7	92	3.8	3.1	0.7

Table 2 Performance of AOGCMs for rainfall

Models	Rainfall							
	A2				B2			
	R^2 (%)	*RMSE* (mm)	*MAE* (mm)	*NSE* (dimensionless)	R^2 (%)	*RMSE* (mm)	*MAE* (mm)	*NSE* (dimensionless)
HadCM3	68	20.8	14.6	0.6	58	24.4	18.5	0.4
GFDL R30	63	34.1	24	-0.03	48	32.7	21.9	0
CGCM2	<u>70</u>	<u>19</u>	<u>14.9</u>	<u>0.6</u>	<u>67</u>	<u>19.7</u>	<u>15.7</u>	<u>0.6</u>
CSIRO MK2	71	24.5	19.7	0.4	71	24.5	19.7	0.4
CCSR-NIES	87	35.3	28	-0.1	87	35.3	28	-0.1

the HadCM3 and CGCM2 models for temperature and rainfall under emissions scenarios A2 and B2 are listed in Tables 1 and 2, respectively. The HadCM3 and CGCM2 models were chosen to simulate temperature and rainfall variables, respectively. Climate change projections for temperature and rainfall were calculated for the future periods 2040–2069 and 2070–2099. The results are listed in Table 3, where it is seen the climate change projections for temperature in the future period 2070–2099 compared to the 2040–2069 exhibit rising temperature compared to the baseline period. Also, there is a lower increase in temperature for emissions scenario B2 compared to the emissions scenario A2. Concerning climate change projections of rainfall the B2 scenario exhibits less variation than scenario A2.

3.2 Simulation of Surface Water Resources

Temperature, rainfall, and runoff in the baseline period served to calibrate the IHACRES model in the period 1971–1990 ($R^2=68\%$, $RMSE=4.9$ m^3/s and $NSE=0.7$), and it was verified in the period 1991–2000 ($R^2=67\%$, $RMSE=5.7$ m^3/s and $NSE=0.6$). The future runoff was projected after ensuring the proper predictive skill of IHACRES model. The average monthly long-term runoff in the baseline period and corresponding to the A2 and B2 emission scenarios in both future periods is shown in Fig. 4. It is evident in Fig. 4 that, in general, in the spring, summer, and mid-autumn of all scenarios there would be a decrease in the surface flow, whereas in the winter and late autumn, in some instances, there would be an increase in future flow. Streamflow under emissions scenario B2 is less than that corresponding to the A2 emissions scenario. The period 2070–2099 would have a larger decrease in streamflow than 2040–2069.

Table 3 Climate change scenarios of temperature and rainfall under emission scenarios

Periods	Temperature (°C)	Rainfall (%)
A2-2040–2069	1.49 to 3.68	-45.6 to 20.1
B2-2040–2069	1.52 to 3.62	-48 to 47.8
A2-2070–2099	2.29 to4.67	-50.4 to 240
B2-2070–2099	2.29 to4.67	-26.9 to 22.5

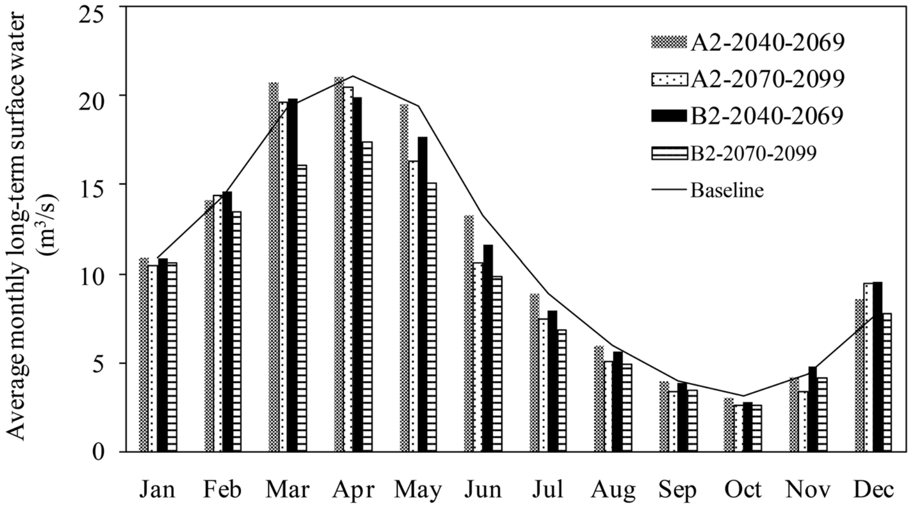


Fig. 4 Average monthly long-term runoff in the baseline period and corresponding to several climate change scenarios

Table 4 Scenarios for water demand assessed with the WEAP system

Scenario	Emission scenario	Increase of agricultural demand	Increase of drinking-industry demand	Period
1	A2	10	20	2040–2069
2	B2	10	20	2040–2069
3	A2	10	30	2070–2099
4	B2	10	30	2070–2099
5	A2	20	20	2040–2069
6	B2	20	20	2040–2069
7	A2	20	30	2070–2099
8	B2	20	30	2070–2099
9	A2	30	20	2040–2069
10	B2	30	20	2040–2069
11	A2	30	30	2070–2099
12	B2	30	30	2070–2099
13	A2	40	20	2040–2069
14	B2	40	20	2040–2069
15	A2	40	30	2070–2099
16	B2	40	30	2070–2099
17	A2	50	20	2040–2069
18	B2	50	20	2040–2069
19	A2	50	30	2070–2099
20	B2	50	30	2070–2099
21	A2	60	20	2040–2069
22	B2	60	20	2040–2069
23	A2	60	30	2070–2099
24	B2	60	30	2070–2099

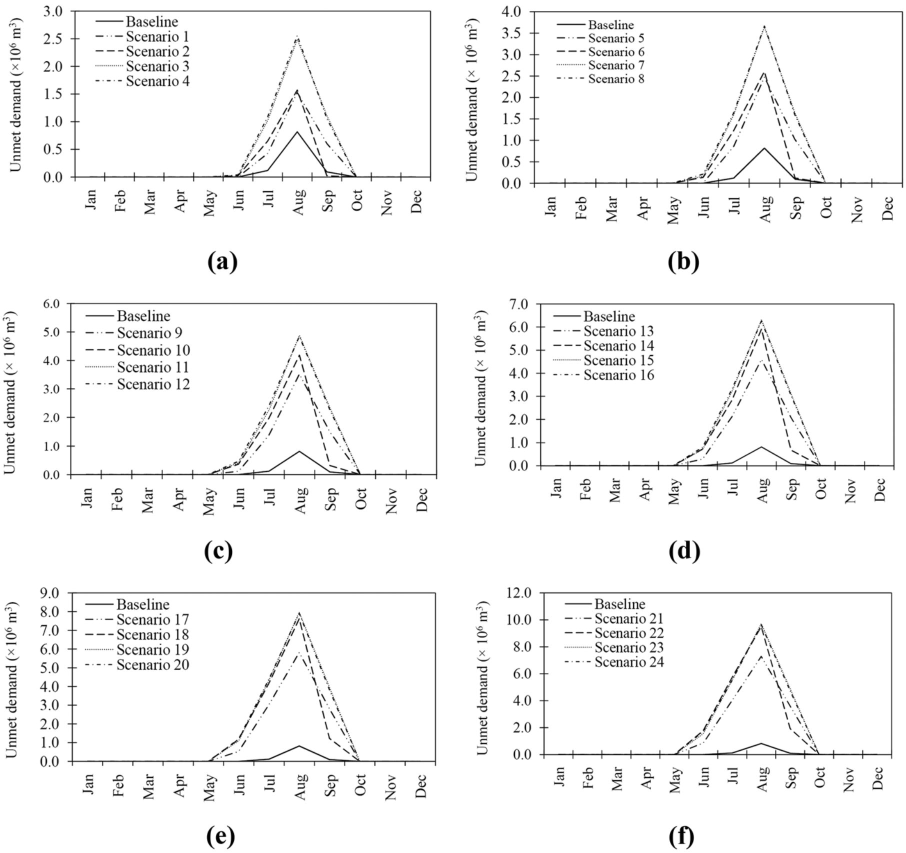


Fig. 5 Unmet water demand associated with agricultural sector corresponding to scenarios **a**-**f** 1 to 24

3.3 Simulation of Groundwater Resources

The changes in groundwater recharge rates in the scenarios A2-2040–2069, B2-2040–2069, A2-2070–2099, and B2-2070–2099 were decreased 1.4, 2.8, 5.7, and 7.1% compared to the baseline period, respectively, indicating a larger decline in recharge in the far future than in the near future. Also, larger reduction of recharge is projected under the B2 emissions scenario than under the A2 scenario.

3.4 Simultaneous Simulation of Surface Water and Groundwater Resources with WEAP System

The effect of climate change on water demand was assessed with the WEAP method by creating scenarios defining 10, 20, 30, 40, 50 and 60% increase in agricultural demand (for the two future periods), and 20 and 30% increase in M&I demand for the periods 2040–2069 and 2070–2099, respectively, relative to the baseline period. These changes in water demand

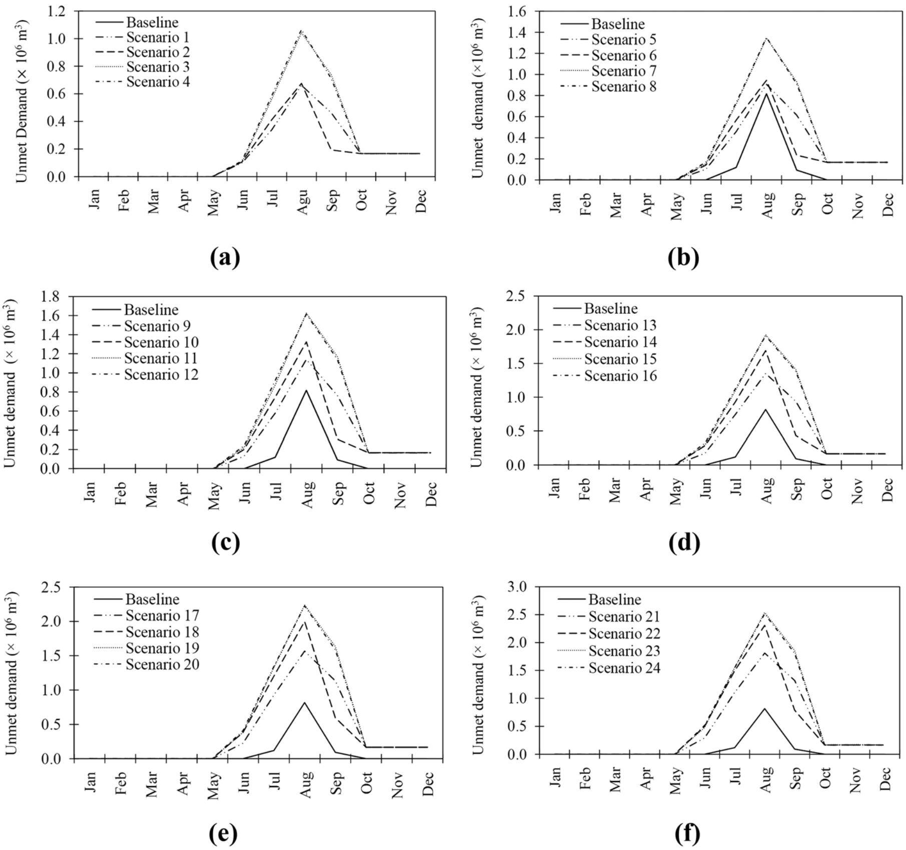
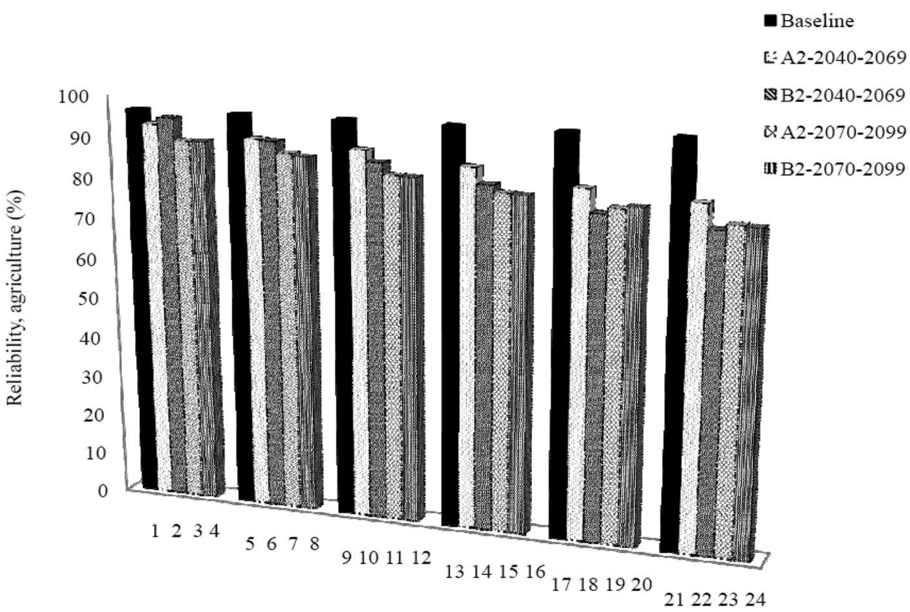
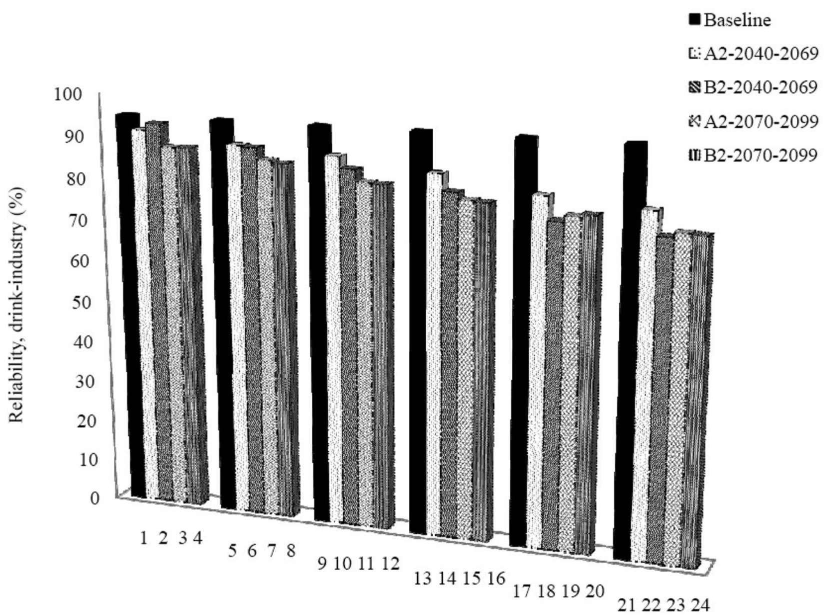


Fig. 6 Unmet demand associated with the M&I sector corresponding to scenarios **a**-**f** 1 to 24

were applied to the future periods and emissions scenarios giving rise to 24 analysis scenarios listed in Table 4. The unmet water demands corresponding to the 24 scenarios in the agricultural and M&I sectors are shown in Figs. 5 and 6, respectively. Figures 5 and 6 indicate an increase in unmet demand in each of the 24 scenarios. It also indicates a shortage of water from late spring to early autumn for the agricultural sector. The failure period of unmet water demand starts in late spring and continues until the end of the autumn for the M&I sector. The unmet demand for the period 2070–2099 is larger than that of 2040–2069. The unmet water demand corresponding to emissions scenario B2 exceeds that of emissions scenario A2. It follows from Figs. 5 and 6 the unmet water demand in Fig. 5 (which concerns the agricultural sector) is higher than the unmet demand in Fig. 6 (which concerns the M&I sector). The unmet water demand for the agriculture and M&I sectors increases with increasing water demand. Figure 7 displays the water reliability index for different climate change scenarios and for the baseline period with respect to the agricultural and M&I sectors. It is seen in Fig. 7 that the reliability of the system associated with the 24 water-demand scenarios is reduced relative to the baseline period in the case of the agricultural and M&I sectors. The system reliability decreases with increasing water demand.



(a)



(b)

Fig. 7 Reliability index in corresponding to different climate change scenarios and the baseline period for **a** agricultural and **b** drinking-industry (M&I) sectors

Table 5 Basic parameters for the IWO, PSO, and SFL algorithms

Parameter	Value
nVar	3
MaxIt	1000
nPop	200

Table 6 Results of the IWO, PSO, and SFL algorithms for Sphere, Ackley, and Rosenbrock functions

Function	Algorithm	Run Time	Best Cost
Sphere	IWO	3.92	7.56E-09
	PSO	7.73	5.99E-91
	SFL	36.32	1.00E-25
Ackley	IWO	3.76	2.65E-04
	PSO	9.2	8.88E-16
	SFL	43.08	2.65E-04
Rosenbrock	IWO	6.28	2.21E-06
	PSO	10.57	8.76E-14
	SFL	44.80	2.21E-06

Table 7 Parameters of the IWOA algorithm

Parameter	Value
Maximum number of iterations	MaxIt = 3000
Maximum population size	nPop = 50
Minimum number of seeds	Smin = 0
Maximum number of seeds	Smax = 5
Decrement component	Exponent = 2
Initial deviation	sigma_initial = 1
Final deviation	sigma_final = 0.001
Number of decision variables	nVar = 360

3.5 Testing the IWOA with Mathematical Functions

Three mathematical functions, namely Ackley, Rosenbrock, and Sphere were used in this study to test the optimizing Capacity of the IWOA in comparison with Particle swarm optimization (PSO) and the Shuffled Frog Leaping (SFL) algorithms. The basic parameters for the IWO, PSO, and SFL algorithms are shown in Table 5. The results of the IWO, PSO, and SFL algorithms for Sphere, Ackley and Rosenbrock functions are listed in Table 6.

The results of Table 6 establish that the IWO algorithm has the capacity to achieve the optimal solution in shorter time for all three functions compared to the other two algorithms. It should be noted that the run time of this algorithm is in all cases close to one half of those by the other algorithms, which demonstrates the rapid convergence of this algorithm.

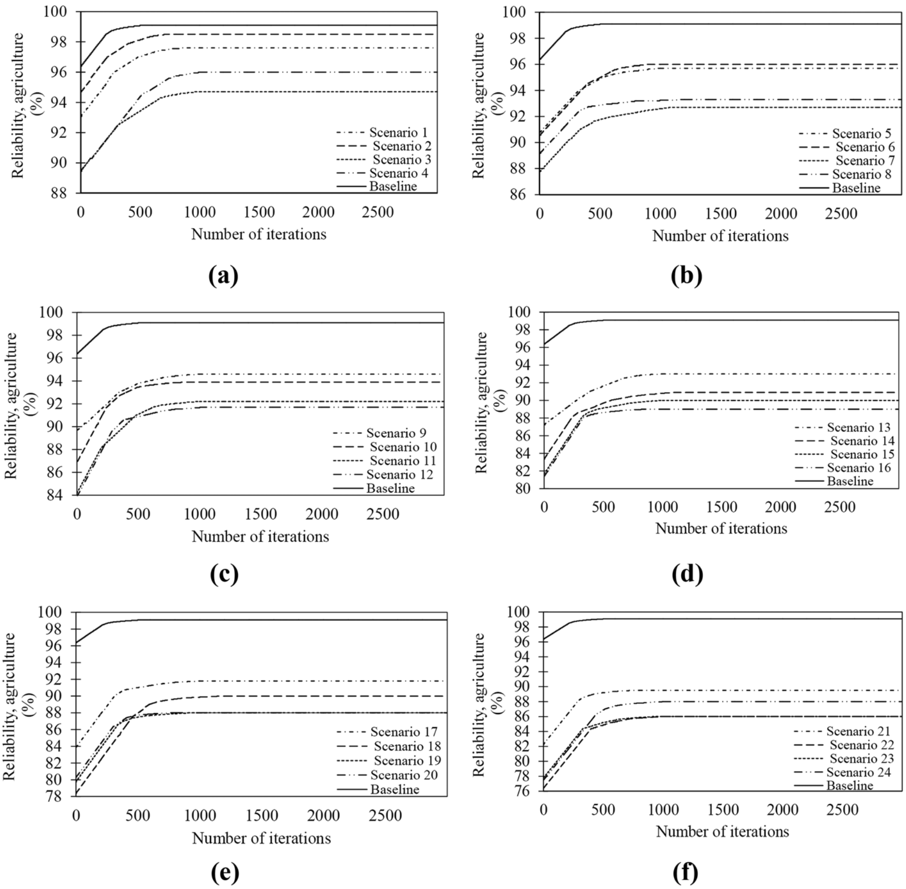


Fig. 8 Comparison of the optimal reliability index corresponding to the baseline period and 24 scenarios with respect to the agricultural sector (**a**)-(**f**)

3.6 Integration of the WEAP System and the IWOA for Optimal Water Allocation

Optimization of the objective function of maximizing the reliability of water allocations for the baseline and the 24 scenarios of increased water demand, emissions scenarios, and future periods was performed employing the IWOA, whose parameters are listed in Table 7. The optimization results are presented in Figs. 8 and 9, which show increases of the objective function for the agricultural and M&I sectors in the future period 2070–2099 compared to the period 2040–2069. It was found the A2 and B2 emission scenarios would lead to better performance in 2040–2069 and 2070–2099, respectively. Scenario 18 had the best performance among the 24 scenarios with a 16.1% increase in the objective function for the M&I sector, and a 14.9% increase in the objective function with respect to the agricultural sector. It is noteworthy that as water demand increases so do the changes in the objective function for both the agriculture and the M&I sectors.

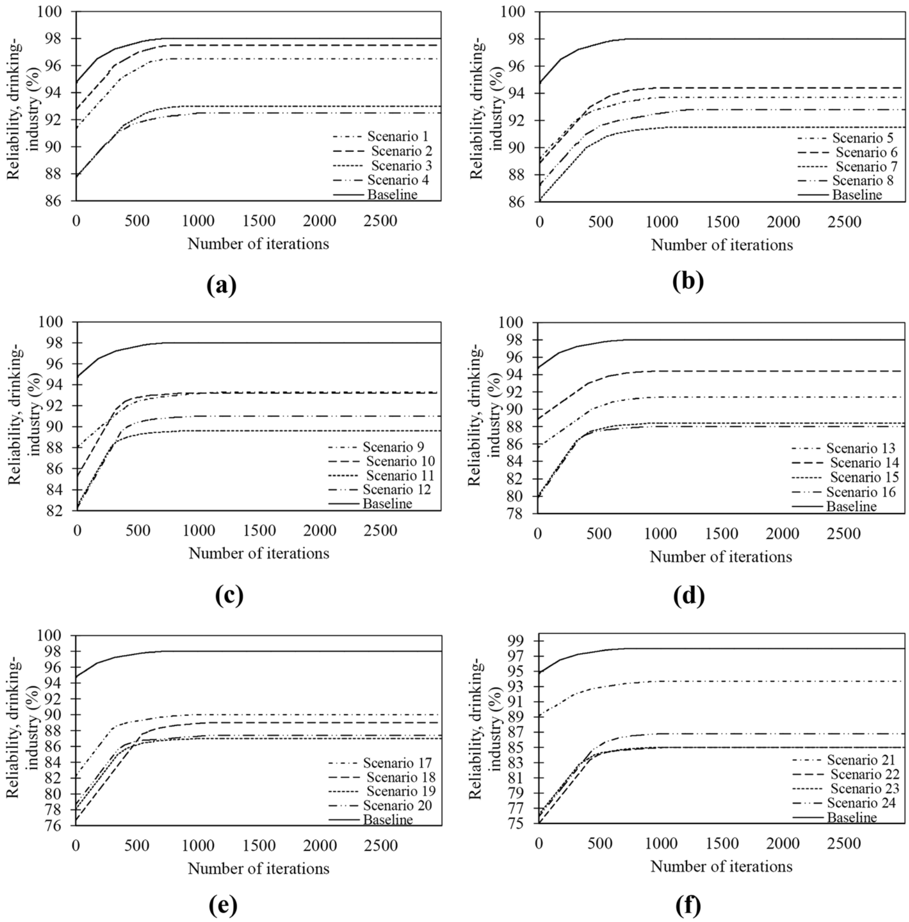


Fig. 9 Comparison of the optimal reliability index corresponding to the baseline period and 24 scenarios with respect to the M&I sector (**a**)-(**f**)

The optimization results for water-allocation reliability shows that the convergence rate is high for the agriculture and M&I sectors during the baseline periods and for most scenarios, so that after 700 to 900 iterations the objective function reaches near constant values. The percentage of optimal reliability changes corresponding to the baseline period and the 24 scenarios for agricultural and M&I water demands are listed in Table 8. The Table 8 results in conjunction with Figs. 8 and 9 show the range of system reliability changes for agricultural water demand associated with the baseline period ranges between 96 to 99%, and it ranges between 76 and 98% for the 24 scenarios. The change in system reliability associated with the M&I sector during the baseline period ranges between 95 to 98%, and it ranges between 75 to 98% for the 24 scenarios. It is concluded the higher the percentage increase in water demand, the greater the percentage change in system reliability. The percentage change in system reliability in 2070–2099 would exceed that in 2040–2069.

Table 8 Percentage change in optimal reliability

Scenario	Agricultural	Drinking-industry
Baseline	2.8	3.5
1	3.9	5.1
2	4.9	5.6
3	5.9	6
4	7.3	5.4
5	6	6.2
6	5.7	5.1
7	5.6	6.3
8	8	9.3
9	6.2	7.1
10	5.4	6
11	9.6	8.6
12	9.7	10.7
13	9.1	10.2
14	6.6	6.8
15	10.2	10.5
16	9.4	10.4
17	14.9	16.1
18	9.4	9.5
19	10.4	11.5
20	9.6	11.2
21	12.6	13.3
22	8.9	9.7
23	10.5	11.7
24	13.6	14.8

The optimal water allocations associated with the baseline period and the 24 scenarios are depicted in Figs. 10 for the agricultural sector and in Figs. 11 and 12 for the M&I sector. It is evident from Figs. 10 and 12 that the optimal water allocations vary in the agricultural and M&I sectors according to the availability of water and the level of water demand throughout the year's seasons. It was determined the water allocations to the agricultural and M&I sector increase with increasing water demand. The water allocations to the agricultural and M&I sectors would be larger with respect to the 24 scenarios than those associated with the baseline period in all months.

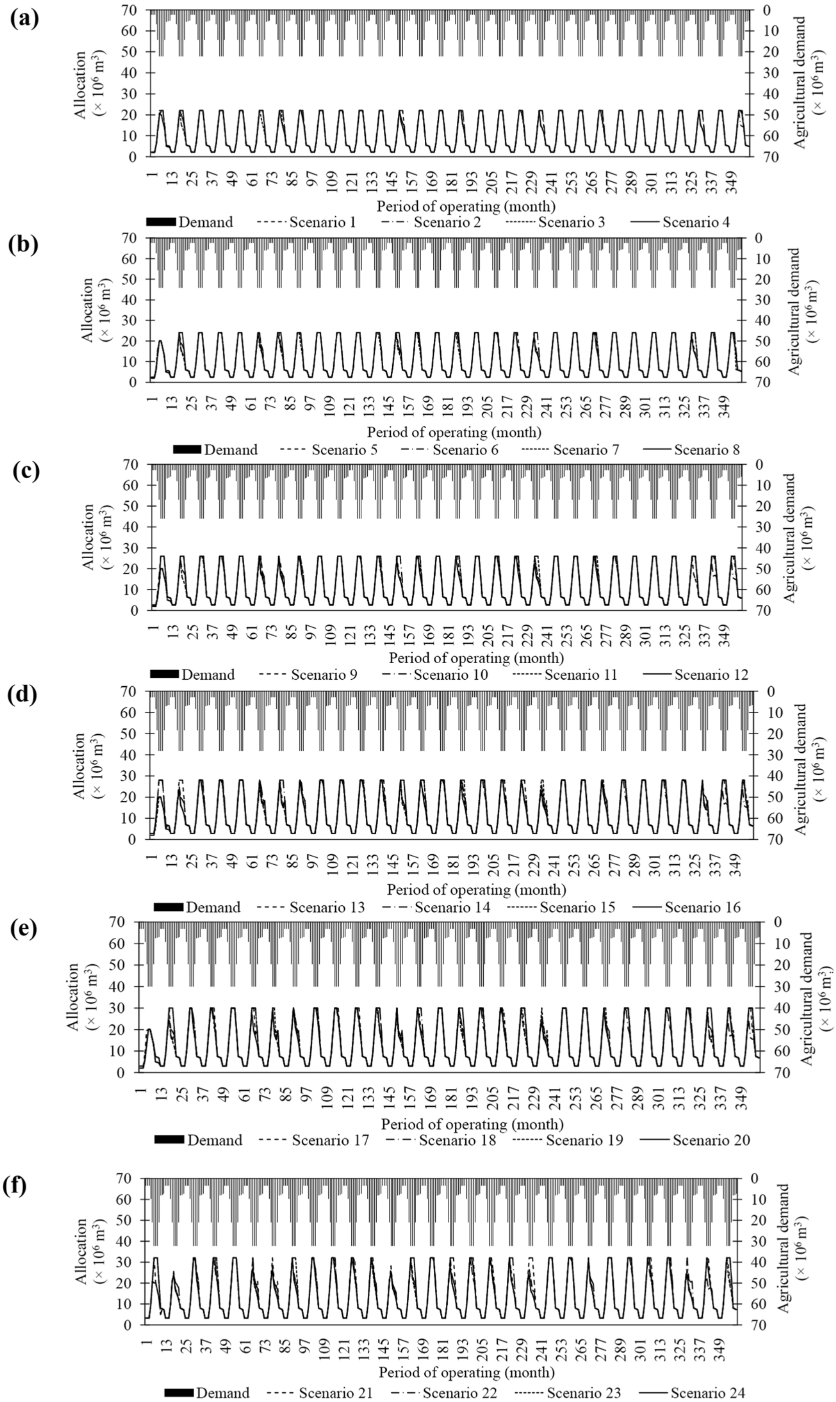


Fig. 10 The optimal allocation of water to the agricultural sector (from surface water and groundwater resources) in scenarios **a** 1 to 4, **b** 5 to 8, **c** 9 to 12, **d** 13 to 16, **e** 17 to 20, **f** 21 to 24 (in 10^6 m.^{3})

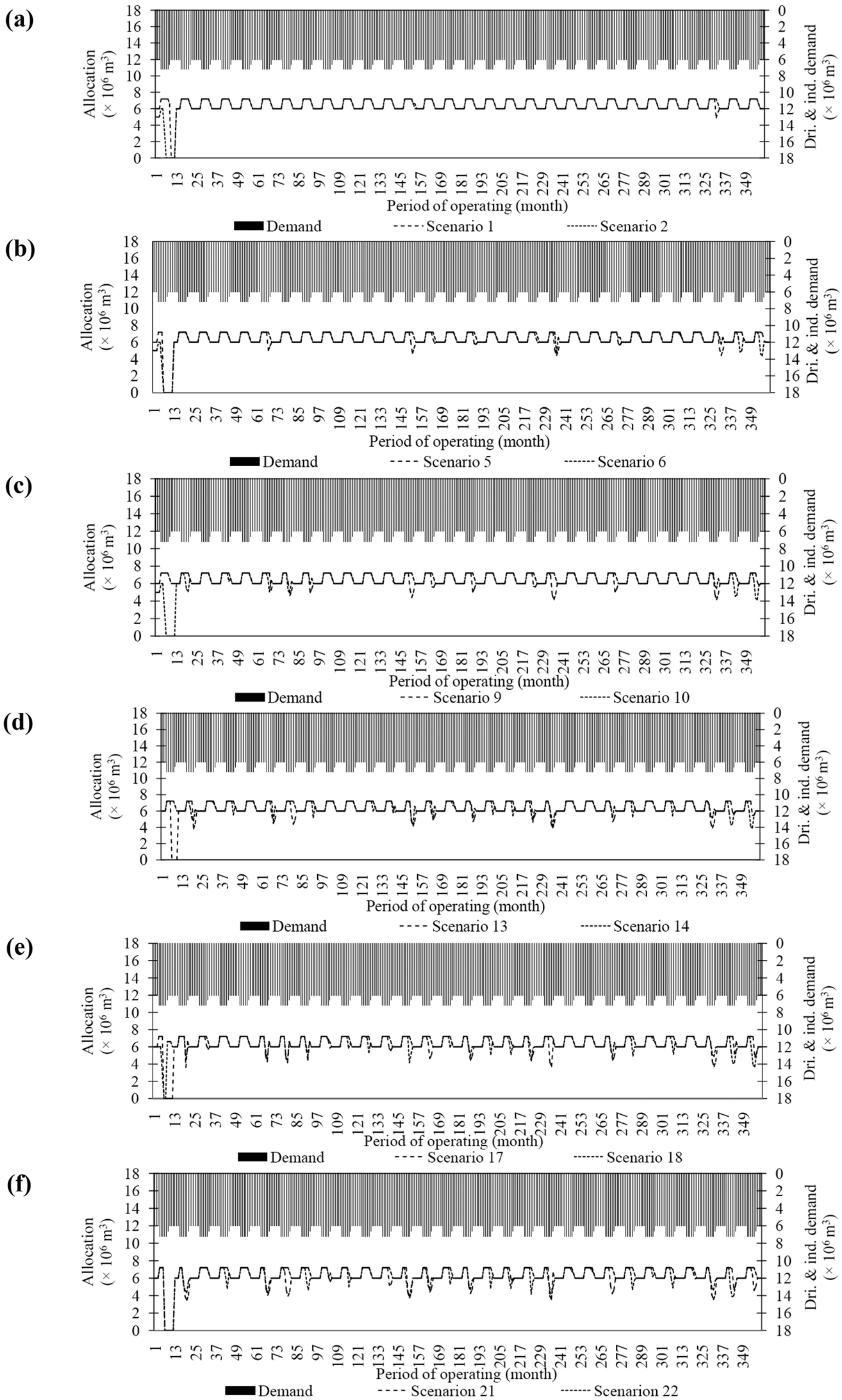


Fig. 11 The optimal allocation of water to the M&I sector (from groundwater) associated with scenarios **a** 1 and 2, **b** 5 and 6, **c** 9 and 10, **d** 13 and 14, **e** 17 and 18, **f** 21 and 22 (in 10^6 m.^{3})

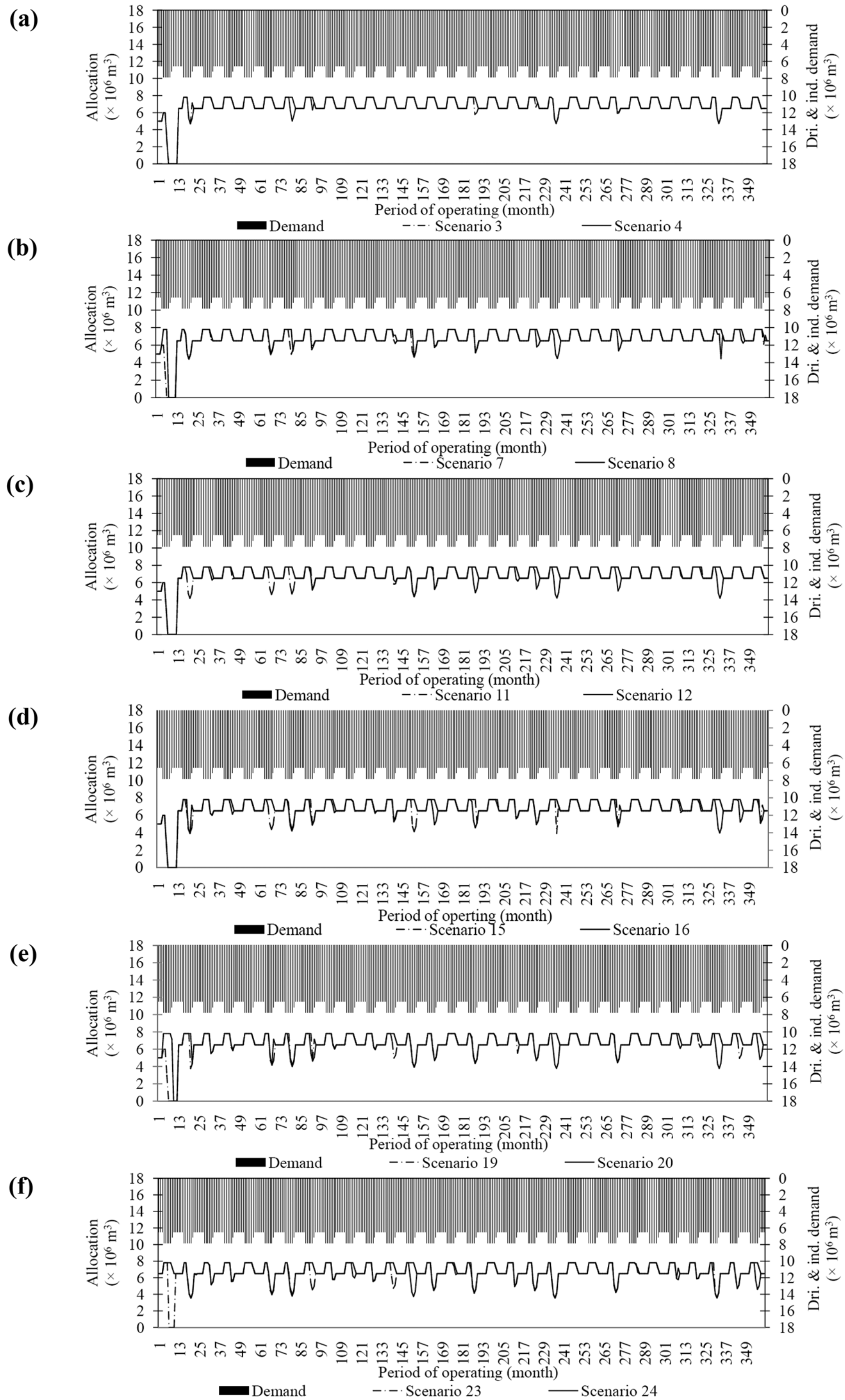


Fig. 12 The optimal allocation of water to the M&I sector (from groundwater) associated with scenarios **a** 3 and 4, **b** 7 and 8, **c** 11 and 12, **d** 15 and 16, **e** 19 and 20, **f** 23 and 24 (in 10^6 m^3)

4 Concluding Remarks

This work applied the invasive weed optimization algorithm (IWOA) to implement a conjunctive optimization model under various climate change scenarios. The WEAP system and the IWOA were combined to determine the optimal operating policies the conjunctive use of water resources in the Khoramabad basin under climate change conditions. Outputs from five AOGCMs were employed under the A2 and B2 emission scenarios during the baseline period 1971–2000, 2069–2070, and 2070–2099 to assess the effect of climate change on basin water supply. The results showed superior performance of the HadCM3 and CGCM2 models for simulating surface temperature and rainfall, respectively. The surface temperature under the scenarios A2-2040–2069, B2-2040–2069, A2-2070–2099, and B2-2070–2099 would increase by 1.5–3.7, 1.5–3.6, 3–7.2, and 2.3–4.7 °C, respectively. The ranges of rainfall change under the scenarios A2-2040–2069, B2-2040–2069, A2-2070–2099, and B2-2070–2099 would -45.7 to 20.4%, 47.9 to -48%, -50.4 to 240%, and -26.9 to 22.6%, respectively. The results of the calibrated and verified IHACRES model would reduce the future long-term annual runoff under the scenario of A2-2040–2069, B2-2040–2069, A2-2070–2099, and B2-2070–2099 about 2, 4, 7, and 9%, respectively. The simulation of groundwater was performed with the GMS calibrated software. The GMS results showed a reduction in groundwater level and recharge relative to baseline values associated with climate change scenarios. The scenarios A2-2040–2069, B2-2040–2069, A2-2070–2099 and B2-2070–2099 would reduce recharge by 1.4, 2.9, 5.7, and 14.5%, respectively, relative to the baseline values. The IHACRES and GMS results were input to the WEAP method and assessed under 24 combined scenarios of water demand and climate change. The 24 scenarios of climate change with the assumption of increasing agricultural demand by 10 to 60% and increasing M&I demand by 20 and 30% in the periods 2040–2070 and 2070–2070 relative to the baseline, respectively, were employed to simulate the status of water resources in the study basin. The water-allocation reliability of the water-resources system was calculated for the M&I and agricultural sectors. It was revealed that under the climate change scenarios there would be a reduction in the system's reliability for both the M&I and agricultural sectors. Optimizing the conjunctive use water resources relied on the IWOA to maximize the river basin system's water allocation reliability. The reliability for the agricultural sector in the baseline period increased by 3%, and that associated with the 24 scenarios increased between 3 to 15relative to the baseline period; the water allocation reliability for the M&I sector in the baseline period was by 3%, and that associated with the 24 scenarios increased between 4 to 16% relative to the baseline period.

The availability of water resources (both surface and ground water) and water demand (including the agriculture, municipal and industrial sectors) will transition under climate change. Adaptation to climate change calls for adopting modified management policies, including reducing the area under cultivation, changing the cultivation pattern, increasing irrigation efficiency in the agricultural sector, and water reuse, and factoring virtual water in the regional water balance.

Future research efforts to supplement this work's findings are:

1. Consider climate change uncertainties should be considered in future climate-change studies. The fourth or fifth IPCC reports can also be used instead of the third report for the purpose of climate projections.
2. Future climate change studies should evaluate other emission scenarios such as A1, B1, etc., besides the A2 and B2 emission scenarios examined in the present study, and the results from multiple scenarios should be compared.

3. The amount of future water use can be calculated with water-demand models such as Cropwat.
4. Surface flow simulation, in addition to the IHACRES model used in the present study, other surface flow models such as HECHMS, SWAT, could be implemented for comparison purposed and uncertainties should be considered.
5. Other optimization algorithms such as the GA, Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Artificial Fish-Swarm (AFS), Bat Algorithm (BA) should be implemented besides the IWOA algorithm for comparison purposes and to evaluate the robustness of results with respect to the choice of optimization algorithm.

Authors Contributions Seyedeh Hadis Moghadam developed the theory and performed the computations. Parisa-Sadat Ashofteh verified the analytical methods and encouraged Seyedeh Hadis Moghadam to investigate a specific aspect. Parisa-Sadat Ashofteh supervised the findings of this work. All authors discussed the results and contributed to the final manuscript. Seyedeh Hadis Moghadam wrote the manuscript with support from Parisa-Sadat Ashofteh, and especially Loáiciga. Parisa-Sadat Ashofteh conceived the original idea.

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Declarations

Conflict of Interest None.

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