



Assessing Adaptability of Cyclic and Non-Cyclic Approach to Conjunctive use of Groundwater and Surface water for Sustainable Management Plans under Climate Change

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Abstract

Groundwater overdraft in many regions throughout the world has been threatening the sustainability of this valuable resource. It has been argued that climate change may contribute to the severity of the issue; hence “impact assessment” is being replaced by “adaptation,” which explores more adapting scenarios and approaches. This study explores the adaptability of the proposed cyclic and non-cyclic conjunctive use of groundwater and surface water resources in increasing groundwater sustainability while increasing the sustainability of water allocation to the agricultural sector under possible climate change scenarios. To simulate climate change in the study area, precipitation and temperature variables are extracted from the results of three global atmospheric circulation models (Ensemble, CMCC-CMS, MRI-CGCM3) under RCP2.6 and RCP8.5 greenhouse gas emission scenarios in the period of 2021–2031. Spatial downscaling is performed using the M5 decision tree algorithm. The Wavelet-M5 hybrid model is used to predict runoff values as a rainfall-runoff model. Also, the Kharrufa method is applied to calculate evaporation in the future seasons. The system’s adaptability to climate change is examined using the multi-objective cyclic and non-cyclic conjunctive use of surface and groundwater models. The study reveals that cyclic operation strategy improves the conjunctive use system adaptability compared to the optimal operation strategy that employs the non-cyclic approach. In this study’s case study, the improvement in groundwater sustainability index exceeds 27 percent over the non-cyclic conjunctive use strategy.

Keywords Climate Change · Adaptation · Sustainability Index · Groundwater Sustainability · Cyclic and Non-Cyclic Conjunctive Use

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1 Introduction

Global warming followed by climate change is currently one of the most important concerns of human societies because this phenomenon causes multiple, severe, and long-term droughts, especially in arid and semiarid regions (Molajou et al. 2021a). Many studies emphasize on the importance of groundwater as a reliable resource under these circumstances (Bloomfield et al. 2019; Cuthbert et al. 2019). However, weakly managed groundwater use may have caused irreparable damage in many parts of the world, such as land subsidence, saltwater intrusion, and unsustainable development (Park and Aral 2004; Rahmati et al. 2019). Therefore, the development and implementation of sustainable groundwater management plans are inevitable, considering the upcoming climatic conditions (Sayed et al. 2020).

A review of the climate change literature shows that in recent years, the focus of studies on its effect on the groundwater is shifting from "impact assessment" to "adaptation" (Kolokytha and Malamataris 2020; Shah 2009). Adaptation strategies include a wide range of interventions, one of which is "preventing losses." This strategy includes a set of adaptation measures to eliminate or reduce the effects of climate change (Nourani et al. 2020). In fact, given the wide range of potential effects of climate change, as well as their inherent uncertainties, adaptation plans, including sustainable groundwater management plans, should be designed to have maximum flexibility. To select the best plan, one may use the multi-criteria analysis method after assessing the plans for future changes (Ehteram et al. 2018; Golfam et al. 2019).

Sustainable groundwater management may refer to its exploitation and use for the present needs while maintaining the resource for future generations without unacceptable environmental, economic, and social consequences (Miro and Famiglietti 2019). Studies to achieve sustainable groundwater management are mainly divided into three categories: supply-side measures (Chakraei et al. 2021; Song et al. 2020), demand-side measures (Afshar et al. 2020b; MacEwan et al. 2017), and a combination of supply and demand-side measures (Jha et al. 2020). In this regard, simulation–optimization models have been widely used to simulate the lumped or distributed aquifer and other components of the supply and demand system and optimize the research objectives (Kerebih MS and Keshari 2021; Jha et al. 2020; MacEwan et al. 2017; Dehghanipour et al. 2020; Medellín-Azuara et al. 2015; Chakraei et al. 2021).

Conjunctive use of groundwater and surface water resources can be considered as one of the supply-side measures to achieve sustainable groundwater management (Song et al. 2020). Cyclic and non-cyclic storage systems (as referred to the CSS and NCSS in this paper, respectively) are two types of conjunctive use systems that have a different attitude to the aquifer recharging (Afshar et al. 2020a; Khosravi et al. 2020; Jahanpour et al. 2015). The exchange of regulated water between surface reservoir(s) and groundwater aquifer(s) is the key component of a CSS that differentiates it from the NCSS as usually practiced (Afshar et al. 2020a).

In NCSS, the release from the reservoir is intended to satisfy downstream water demands such as municipal, industrial, irrigation, and environmental demands (Khosravi et al. 2020). The diversion for artificial groundwater recharge is often allowed from spilled water to reduce cost and water loss from the basin when the reservoir is full (Hashemi et al. 2015; Hamamouche et al. 2017). In the more common approach to conjunctive use of surface and groundwater, it is believed that the use of regulated water as a source for groundwater recharge is not economically viable, and in many regions, artificial recharge

through floodwater capture is likely to be a primary component of the region's groundwater management strategy (Hashemi et al. 2015; Nayak et al. 2018; Joodavi et al. 2020; Khosravi et al. 2020).

As a novel strategy, the current study explores the best supply-side measures, employing cyclic and non-cyclic conjunctive use strategies to achieve sustainable groundwater management under different climate change conditions. The study uses a cyclic and non-cyclic multi-objective conjunctive use of surface and groundwater management to assess system adaptation to different climate change conditions. The models intend to i) minimizing the total square deviations from the target water table (*DTWT*) ii) maximizing the sustainability index (*SI*) under different climate scenarios. The sustainability index was used in this study to evaluate water supply plans for future water availability in the agriculture sector, considering measures of reliability, resilience, vulnerability (Sandoval-Solis et al. 2011). The unit response matrix method for point, linear, and distributed excitations is used to simulate the aquifer's response to any trial solution generated by the optimization model. Climate scenarios are derived from the Ensemble, CMCC-CMS, and MRI-CGCM3 global climate models, and the M5 decision tree algorithm is used to downscale the climatic data. The runoff and evaporation for the future simulation period have been estimated using the Wavelet-M5 hybrid model (Nourani et al. 2019a, c) and the Kharrufa method (Kharrufa 1985), respectively. The proposed solution methodology for the multi-objective optimization employs an ϵ – Constraint approach to develop the Pareto fronts for the non-convex, nonlinear cyclic, and non-cyclic models. The findings of this paper can help the groundwater management authorities to select the appropriate strategies for groundwater adaptation to anticipated changes in climate conditions.

2 Methodology

2.1 Conceptual of the CSS and NCSS

CSS models consist of four basic subsystems: surface reservoir, aquifer, river, and demand site subsystems that can interact cyclically (Afshar et al. 2020a). Figure 1 shows the main components of a CSS. As shown in Fig. 1, reservoir storage (S^s) volume the inflow to the reservoir, (Q^s) precipitation (Prc), spill from the reservoir (Spill), water transfer from the aquifer to the reservoir (R_a^s), the amount of water directly transferred to the demand area and/or recharging sites (R_{ar}^s) evaporation from the reservoir (E^s) and the release from the surface reservoir to the river (R_{riv}^s) constitute the volume balance components of the dam. Groundwater recharge in the CSS occurs from dam, river diversion (Div_{ar}) stream seepage (Q_{ar}^{riv}) deep percolation of irrigation water, natural recharge from infiltrated precipitation ($Seep$). The municipal and agriculture demands are met through groundwater pumping (R_d^s), direct transfer from the reservoir (R_d^s) and river diversion (Div_d). In Fig. 1, are the surface water leaving the system's boundary and the return flow from demand sites to the river reaches, respectively. Along the watercourse, there is hydraulic interaction between river and aquifer, causing seepage from the aquifer to the river, or vice versa, that shown in Fig. 1 with Q_{ar}^{riv} .

In the NCSS strategy, on the other side, the regulated water is never used for direct recharge of the aquifer, and artificial recharge is limited to river diversion during wet operational seasons with a spill from the surface reservoir.

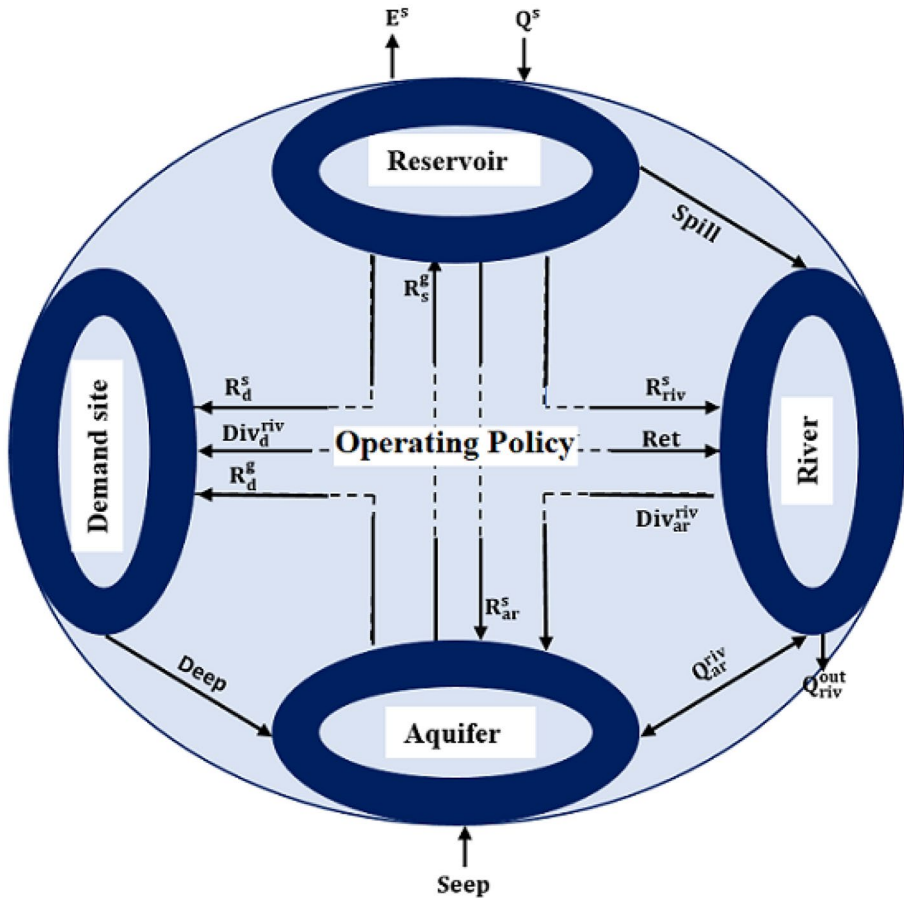


Fig. 1 The main components of a CSS

2.2 Study Region and Basic Data

2.2.1 Hydrological and Hydraulic Data

The study region encompasses the Kinevars dam and its downstream watershed of Abhar River, which is located at Zanjan Province in Iran. Kinevars Dam has been constructed to store water for municipal water supply in Abhar County as well as agricultural development. The annual water demand of municipal and agricultural areas is 26 MCM. Agriculture is the predominant user of surface and groundwater in the region (15.6 MCM per year). Unfortunately, in the study area, climate change and poor basin management have caused severe and frequent dry and wet years, and principled management will be the main solution to reduce the problems ahead. Groundwater is used conjunctively with surface water for agricultural and municipal water supply purposes in the region. Given that groundwater velocity in the area is slower than that of surface water, the seasonal model has been preferred to the monthly operation model.

The aquifer area is 80 square kilometers. The initial water table in wells is 20 m. According to the operation studies of Abhar plain conducted by groundwater consultants, the maximum pumping and recharging to the aquifer is 3 MCM/Season. The discharge wells are the best place to recharge the aquifer. In the absence of reliable field data, it is assumed that 10% of seasonal precipitation and 10% of supplied water (both for irrigation and domestic use) percolate into the aquifer.

2.2.2 Climatic Data

In the present study, the results of the Ensemble model have been used for historical simulation of precipitation and temperature under two scenarios RCP2.6 and RCP8.5, in the period 2021–2031 (Her et al. 2016; Tegegne et al. 2019). Furthermore, considering that Abbasian et al. (2019) have shown that CMCC-CMS and MRI-CGCM3 models are the best models for estimating temperature and precipitation in Iran, respectively, these models were used in the current study.

As previously mentioned, precipitation (Prc), the inflow to the surface reservoir (Q^s) and evaporation from it (E^s) are the three input state variables of the cyclic and non-cyclic optimization models. In this study, Prc directly Q^s and E^s are indirectly entered into these optimization models from precipitation-runoff and temperature-evaporation models, respectively. But before doing anything, a spatial downscaling technique must be used for precipitation and temperature data because the spatial resolution of GCM models is very low. The M5 decision tree algorithm is one of these techniques that first divides the data of precipitation and temperature into classes and then fits a regression model into the data of each class (Goyal and Ojha, 2012; Nourani et al. 2019b, 2020). In the current study, 9 points around the study area have been entered into the decision tree model.

2.3 Simulation Models

2.3.1 Temperature-evaporation Sub-model

Many empirical relationships have been proposed to calculate evaporation, which are mainly divided into three categories of temperature, radiation, and humidity-based methods. Ghamarnia and Lorestani (2018) found that the Kharrufa method provided relatively better results than other methods (Ghamarnia and Lorestani 2018). In this study, the Kharrufa method, which is based on air temperature and recommended by Nourani et al. (2020), has been used to calculate the evaporation from the surface reservoir (Kharrufa 1985):

$$ET = 0.34 \times p \times T_a^{1.3} \quad (1)$$

In which ET = the Kharrufa potential evaporation (mm/month), p = the proportion of total monthly daytime hours used out of annual daytime hours of the year and T_a = mean monthly temperature in Celsius.

It should be noted that the simulation time step in this study is seasonal. Therefore, the evaporation height should be calculated seasonally.

2.3.2 Rainfall-runoff Rub-model

The runoff time series is estimated using the Wavelet-M5 hybrid model introduced by Nourani et al. (2019a), which combines the M5 model tree and Wavelet Transform. The proposed hybrid modeling is accomplished in three steps. In the first step (date pre-processing), the time series of runoff ($Q^s(t)$) and precipitation ($Prc(t)$) are decomposed using Wavelet Transform. In the second step (data classification), the decomposed time series are classified into some homogeneous clusters using the M5 model tree. In the third step, the existing patterns between the data in each homogeneous cluster are extracted using the M5 model tree.

It should be noted that the previous studies have shown that the rainfall-runoff process is included both seasonality and autoregressive characteristics (Molajou et al. 2021b). It is obvious that due to the autoregressive feature, the impact of other parameters that are effective in the rainfall-runoff process can be indirectly considered by the prior runoff ($Q^s(t)$) values. In modeling via Wavelet-M5 model, the wavelet used in the current study to catch seasonality of the process can decompose $Prc(t)$ and $Q^s(t)$ into approximation sub-series ($Prc_i(a)$ and $Q_i^s(a)$) and detailed sub-series ($Prc_i(D_i)$) and $Q_i^s(D_i)$). To study the mathematical basics of the hybrid Wavelet-M5 model, the readers are referred to (Nourani et al. 2019a, c).

2.3.3 Groundwater Simulation Sub-model

Based on the type of groundwater simulation model used, groundwater models can be classified as distributed or lumped systems (Afshar et al. 2020a; Alimohammadi et al. 2009; Taormina et al. 2012). Unlike distributed models, in the lumped approach, the spatial distribution of the hydraulic components of the aquifer system is not considered, and the aquifer is modeled as an integrated system. According to the research, distributed models implemented in three methods: 1- embedding the equations governing the flow of groundwater (Gorelick 1983), 2- embedding the aquifer response function such as unit response matrix(URM) method and stepwise regression method (Seo et al. 2018; MacEwan et al. 2017), and 3- iterative data exchange between the groundwater simulation model and optimization model (Medellín-Azuara et al. 2015).

In the first method, the finite differences approximations of the groundwater flow equation are embedded within the optimization model as part of the constraint set. The biophysical response function from a groundwater hydrologic model integrates into an optimization model in the second method. The response functions describe the change in groundwater elevation at different places and times as a function of various variables such as groundwater extraction. Finally, in the third method, the groundwater simulation and optimization models are run separately, and essential data (e.g., change in groundwater elevation) are passed between the models at each time step.

Equation 2 shows the main equation of the URM method, which is obtained from the analytical solution of the Bossinesque equation for point sources (Seo et al. 2018):

$$s(w, n) = \sum_{t=1}^n \sum_{j=1}^{NW} \beta_w(w, j, n - t + 1).q(j, t) \quad (2)$$

In which $s(w, n)$ is the drawdown at well w at the end n^{th} of the time period, $\beta_w(w, j, n - t + 1)$ or unit response coefficient is the change of water table in well w at the end of n^{th} the time period with unit stimuli (pumpage/recharge) at the well j at the end of t^{th} time period, and $q(j, t)$ the amount of stimuli (pumpage/recharge) at well j , and time period t and NW is the total number of pumping wells. In this method, by obtaining the unit response coefficients from the groundwater distribution simulation model (such as MODFLOW), the change in groundwater elevation by excitation at different points and times obtain at different points and times. In practice, there can be three types of stimulation: 1- point stimulation (q) such as discharge/recharge wells, 2- linear stimulation such as depth change of river (dh_{riv}), 3- surface stimulation (P_a) such as deep percolation of irrigation water or precipitation. Given the types of stimuli, Eq. 2 is modified as Eq. 3:

$$\begin{aligned}
 S(w, n) = & \sum_{t=1}^n \sum_{j=1}^{NW} \beta_w(w, j, n - t + 1).q(j, t) \\
 & + \sum_{t=1}^n \sum_{j=1}^{NR} \beta_{riv}(w, j, n - t + 1).dh_{riv}(j, t) \\
 & + \sum_{t=1}^n \sum_{j=1}^{NA} \beta_a(w, j, n - t + 1).P_a(j, t)
 \end{aligned} \tag{3}$$

In which NR and NA are the number of river reaches and surface stimulation, respectively.

The URM method is applicable for confined and unconfined aquifers if the groundwater table changes are negligible versus saturation layer thickness. Otherwise, they can be estimated with acceptable accuracy by using the MURM method. In this paper, the MURM method will be used to evaluate unconfined aquifer response to external stresses (excitations) as proposed by Alimohammadi et al. (2009):

$$s(w, n) = \sum_{t=1}^n \sum_{j=1}^{NW} m_w(w, j, n - t + 1).\beta_w(w, j, n - t + 1).q(j, t) \tag{4}$$

In which $m_w(w, j, n - t + 1)$ is the correction coefficient for excited well w for unit excitation in exciting well j during time period t . In fact, $m_w(w, j, n - t + 1)$ is a correction factor that partially adjusts the nonlinear response of the excited well in an unconfined aquifer.

2.3.4 CSS Simulation Sub-Models

The full-scale CSS simulation model consists of i) surface reservoir simulation module, ii) groundwater simulation module, iii) groundwater-surface water interaction module. This section presents the simulation models of different parts of the CSS as follows:

The surface reservoir simulation model mathematically defines the change of storage within the reservoir considering the seasonal evaporation, inflow to the reservoir, release from

the reservoir to demand site, direct water transfer for artificial recharge, release to the downstream river for municipal, irrigation, and environmental water demands, and uncontrolled spill. Evaporation from the reservoir is estimated using seasonal average reservoir storage and evaporation rate from surface water bodies as:

$$E^s(t) = ep(t).(A^s(t) + A^s(t + 1))/2; \forall t \tag{5}$$

$$A^s(t) = a_0 + a_1 S^s(t); \forall t \tag{6}$$

In which $S^s(t)$ is reservoir storage volume at the beginning of the time step t ; $A^s(t)$ is reservoir surface area corresponding to $S^s(t)$; $ep(t)$ is evaporation height, a_0 and a_1 are the fixed evaporation coefficients.

Demand may be satisfied by one or any combination of water transfer from the surface reservoir, groundwater pumping, and direct diversion from the downstream river to the demand site. The seasonal deficit is defined as:

$$def(t) = Dem(t) - [R_d^s(t) + R_d^g(t) + Div_d^{riv}(t)]; \forall t \tag{7}$$

In which $def(t)$ = water deficit in the agriculture sector; $Dem(t)$ refers to seasonal demand.

The groundwater simulation module addresses groundwater storage and groundwater level change for any trial solution and/or excitation throughout the aquifer. The seasonal change in groundwater storage is estimated as:

$$\begin{aligned} \Delta S^g(t) = & \sum_{w=1}^{NW} q_{ar}(w, t) - \sum_{w=1}^{NW} q_p(w, t) + \sum_{r=1}^{NR} Q_{ar}^{riv}(r, t) \\ & + Deep.Sup(t) + Prc(t).Seep.AQA; \forall t \end{aligned} \tag{8}$$

In which $\Delta S^g(t)$ = seasonal change in the aquifer storage; $q_p(w, t)$ and $q_{ar}(w, t)$ = volume of water recharge to and discharge from the well w , respectively; $Sup(t)$ = seasonal water supply to the irrigated area, AQA = the aquifer surface area; Prc = precipitation depth.

Responses of the aquifer to any excitations are estimated using Eq. 4. The same concept is used for simulating river-aquifer interaction. It considers the river as a linear source/sink term (Alimohammadi et al. 2009). Change of storage and water level in the river is calculated solving Manning equation during each time step for all river segments, considering the lateral inflows and outflows. River cross-sectional area is used to estimate the volume of river water storage in each river segment. Detail of the mathematical representation and procedure may be found in Alimohammadi et al. (2009).

The system simulation model for NCSS is slightly different. As previously mentioned, in non-cyclic operation, the regulated water is not transferred from the surface reservoir to the aquifer. For this reason, in the NCSS, the surface reservoir simulation model only is changed by adding the following equation to the surface reservoir simulation model of CSS.

$$R_s^g(t) = 0; \forall t \tag{9}$$

$$R_{ar}^s(t) = 0; \forall t \tag{10}$$

2.4 Optimization Model

2.4.1 CSS Multi-Objective Optimization Model

This section presents a multi-objective, multi-period nonlinear cyclic model with the conflicting objectives of sustainability index (*SI*) and total square deviations from the target water table (*DTWT*).

The sustainability index used for sustainable water allocation to the agricultural sector is a function of the three performance criteria of reliability (*Rel*), resilience (*RES*) and vulnerability (*Vul*) (Sandoval-Solis et al. 2011):

$$SI = [Rel * Res * (1 - Vul)]^{1/3} \tag{11}$$

Various criteria are used to quantify groundwater sustainability. In this study, minimizing the total deviations from the target level was considered:

$$DTWT = \sum_{w=1}^{NW} \sum_{t=1}^{NT} (h(w, t) - h_{target})^2 \tag{12}$$

In which $h(w, t)$ = water table in well w and time step t and h_{target} = target water table in the basin.

Using the ϵ -constraint method, we optimize one of the objective functions (*DTWT*) using the other objective function (*SI*) as a constraint. In the CSS optimization model, optimal water transfer policies between different subsystems are the decision variables. As such, the cyclic optimization model is presented as follows:

Objective functions:

$$\text{Min DTWT and Max SI} \tag{13}$$

Constraints on the surface reservoir and capacity constraints:

$$S^s(NT + 1) \geq S^s(1) \tag{14}$$

$$S^s(t) \leq CapD; \forall t \tag{15}$$

$$R_j^i(t) \leq Cap^i \tag{16}$$

$$k_d \leq S^s(t); \forall t \tag{17}$$

In which $R_j^i(t)$ = water transmission from subsystem i to subsystem j at time step t , Cap^i = capacity of subsystem i , $CapD$ = capacity of the surface reservoir and k_d = reservoir's dead storage.

Constraints on demand site:

$$def(t) \leq DemAgri(t); \forall t \tag{18}$$

Using Eq. 18, the municipal water demand will be fully met, and only the agricultural sector will suffer from water deficits.

Constraints on aquifer:

$$S^g(NT + 1) \geq S^g(1) \quad (19)$$

$$q_p(w, t) \leq q_p^{max}; w, t \quad (20)$$

$$q_{ar}(w, t) \leq q_{ar}^{max}; w, t \quad (21)$$

$$h^{min} \leq h(w, t) \leq h^{max}, \forall w, t \quad (22)$$

In which q_p^{max} and q_{ar}^{max} = maximum groundwater extraction and recharge rates, respectively; h^{min} and h^{max} = minimum and maximum water table per well.

Constraints on river hydraulics:

$$Q_{riv}^{min}(r, t) \leq Q_{riv}^{out}(r, t) \leq Q_{riv}^{max}(r, t); \forall r, t \quad (23)$$

In which Q_{riv}^{min} and Q_{riv}^{max} = minimum environmental requirement and maximum river capacity, respectively.

2.4.2 NCSS Multi-objective Optimization Model

The non-cyclic model's objective function is similar to CSS. Cyclic and non-cyclic operation models have common constraints. Therefore, the constraints of this model can be obtained by adding the following constraints to the cyclic operation model:

$$R_{riv}^s(t) \leq Div_d^{riv}(t) + CapEn(t); \forall t \quad (24)$$

$$Div_{ar}^{riv}(t) \leq Spill(t); \forall t \quad (25)$$

In which $CapEn(t)$ = environmental demand at time step t . In the NCSS, artificial recharge occurs only in times of spill (constraint 25), and the release from the reservoir is intended to satisfy downstream water demands such as municipal, irrigation, and environmental demands (constraint 24).

3 Results and Discussion

3.1 Climate Change

As mentioned earlier, in the first step, the M5 decision tree algorithm is used to downscale spatial Ensemble, MRI-CGCM3, and CMCC-CMS data for RCP2.6 and RCP8.5 climate change scenarios. For this purpose, 75% of the data are intended for model training, and the remaining data are considered for validation of the trained model. Table 1 shows the downscaling accuracy of monthly precipitation and temperature over the baseline period (1990–2000). According to Table 1, it can be seen that the M5 decision tree algorithm has good performance in downscaling of precipitation and temperature data, which also indicated in previous studies (Goyal and Ojha 2012; Nourani et al. 2019b, 2020).

Table 1 Performance of the decision tree in the baseline period (1990–2000)

	Precipitation				Temperature			
	CC		RMSE** (normalized)		CC		RMSE (normalized)	
	Train	Verify	Train	Verify	Train	Verify	Train	Verify
Ensemble Model	0.74	0.66	0.129	0.143	0.96	0.91	0.056	0.071
MRI-CGCM3	0.81	0.73	0.112	0.134				
CMCC-CMS					0.98	0.93	0.054	0.069

*Correlation Coefficient (CC)

**Root Mean Square Error (RMSE)

After that, as a second step, considering that runoff data should be imported in cyclic and non-cyclic optimization models, the hybrid Wavelet-M5 model was used to extract the rainfall-runoff model (runoff data for future). In this regard, this model was presented using observational precipitation and runoff data, and it is assumed that the resulting model can also be used to predict future data. It should be noted that 75% of the data are intended as a training set, and the remaining data are considered for verification of the model. The calculated criteria for evaluating the model’s efficiency ($CC_{train} = 0.976$ and $CC_{verify} = 0.951$; $RMSE_{train} = 4.167$ MCM and $RMSE_{verify} = 5.083$ MCM) indicated the high performance of the hybrid method for rainfall-runoff modeling.

In the next step, the downscaled precipitation data and also the estimated seasonal data of runoff (using Wavelet-M5 model) and evaporation height (using Kharrufa method) in the future period 2021–2031 (40 seasons) were given to the optimization models as input data (see Fig. 2).

In order to compare the performance of the cyclic and non-cyclic operations, the capacities of different subsystems are assumed to be identical in both approaches. Therefore, considering known capacities for different parts of the CSS and NCSS that

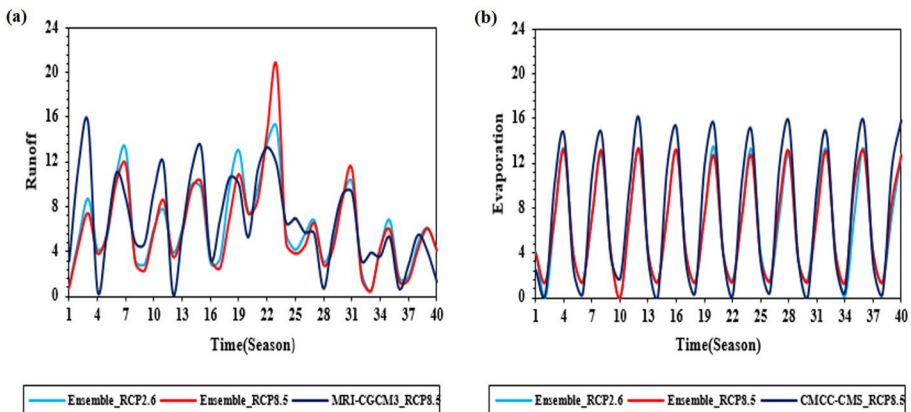


Fig. 2 Seasonal values of (a) Runoff (MCM) and (b) Evaporation (mm) in the 2021–2031

Table 2 Assumed capacities for different subsystems

Component	Capacity
Reservoir	10.5
Transfer from the reservoir to demand site	2.9
Transfer from the reservoir to the artificial recharge area	0
Diversion from the river to demand site	1.8
Diversion from the river to the artificial recharge area	1.2

are shown in Table 2, cyclic and non-cyclic operation models were run for different ϵ values and 40 seasonal time steps.

The unit for reservoir capacity is million cubic meters (MCM); it is MCM/season for others.

After solving the cyclic and non-cyclic optimization models using the ϵ -Constrain method, Pareto solutions were obtained for different climate change scenarios (see Fig. 3). According to Fig. 3, for any given sustainability index (SI), the total square deviations (DTWT) with NCSS well exceeds that of the CSS operation strategy. The sustainability index in the cyclic approach can reach 0.75, although this is associated with more aquifer pumping. However, in the non-cyclic approach, this can be increased up to 0.59. The results show that in critical situations where we have to use less groundwater (DTWT is approximately zero), the cyclic operation of the system will increase the sustainability of water allocation to the agricultural sector by about 10% compared to the non-cyclic operation (See the beginning of the diagrams in Fig. 3).

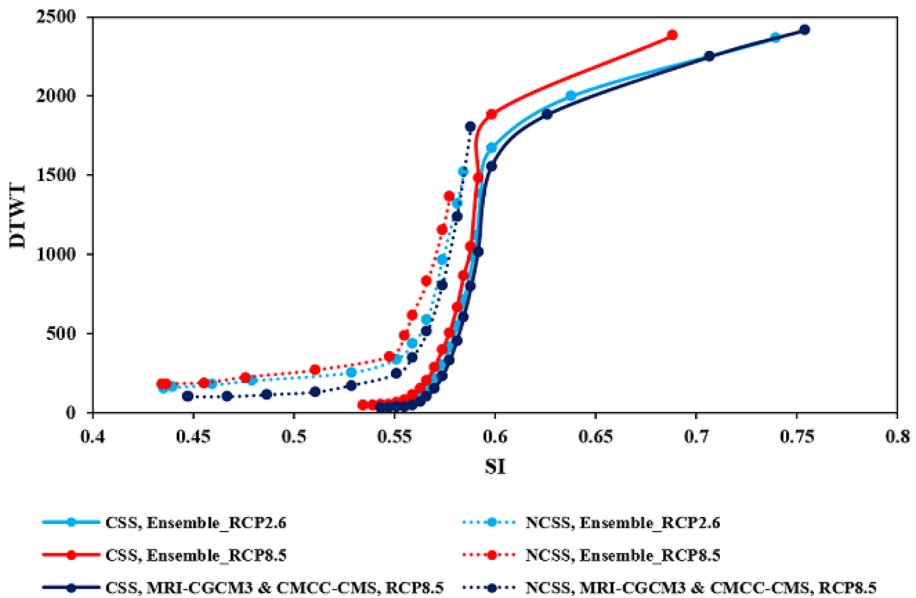


Fig. 3 Pareto solutions of cyclic and non-cyclic operations for Ensemble model in RCP2.6 and RCP8.5, and MRI-CGCM3 & CMCC-CMS models in RCP8.5

Based on the data of three GCM models (Ensemble, CMCC-CMS, MRI-CGCM3), climate change will reduce precipitation and runoff in the study area in the future period (2031–2021). Therefore, if climate change occurs, the natural aquifer recharge and the amount of water available for supply to the demand and artificial recharge areas will decrease. Hence, it seems logical that climate change will reduce aquifer sustainability and sustainability of water allocation to the demand site of the study area.

MRI-CGCM3 model predicts more rainfall and runoff than the Ensemble model. According to the climate change data of the Ensemble model, precipitation and runoff will be lower than when the carbon dioxide emission rate follows the RCP8.5 scenario. Therefore, the results also show that in both cyclic and non-cyclic approaches, system performance is weakening (SI is declining and $DTWT$ is increasing) in the event of scenarios 1- MRI-CGCM3 and CMCC-CMS_RCP8.5, 2- Ensemble_RCP2.6, and 3- Ensemble_RCP8.5, respectively (see Fig. 3).

In the following, for a detailed discussion and comparison of the performances of CSS and NCSS, Sect. 3.2 is presented.

3.2 Towards Groundwater Sustainability with Cyclic or Non-cyclic Strategy

Overall, the key issue of this section is to show why, in the cyclic operation of the system for a sustainability index, the water table is closer to the target level. Therefore, from the set of Ensemble_RCP2.6 Pareto solutions shown in Fig. 3, two cyclic and non-cyclic solutions are selected, and their results are compared. The selected Pareto solutions in the cyclic and non-cyclic approaches are ($SI = 0.585, DTWT = 712$) and ($SI = 0.585, DTWT = 1519$), respectively. Suppose the achievement of the water table of 25 m (target level) and 20 m (initial level) is interpreted as 100 and 0% of aquifer sustainability. In that case, respectively, we achieve 76.3% and 49.4% sustainability in cyclic and non-cyclic strategies.

Figure 4 shows the average groundwater level (h_{avg}) for the two Pareto solutions in 40 seasonal time steps. The highest and lowest water demands are in summer and winter, respectively. For this reason, the local maximum and minimum drawdown occur mainly in the summer and winter seasons, respectively (see Fig. 4). As illustrated, achieving the

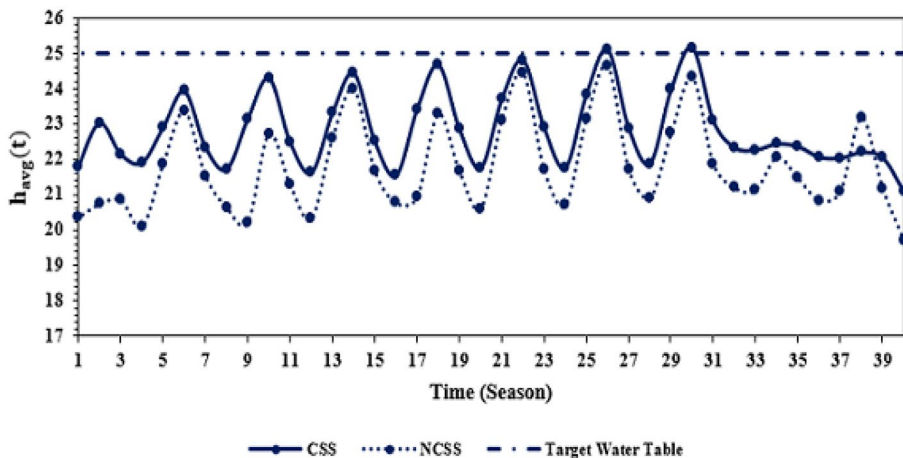


Fig. 4 Comparison of the average water table in cyclic and non-cyclic operation with the target water table

Table 3 Results for Pareto solutions ($SI = 0.585, DTWT = 712$) and ($SI = 0.585, DTWT = 1519$)

Variables	Description	CSS	NCSS
		Volume(MCM)	Volume(MCM)
$\sum Q_{riv}^{out}$	Total surface water leaving the system's boundary	81.50	103.28
$\sum R_d^s(t)$	Total transfer from the surface reservoir to demand site	78.44	69.67
$\sum Div_d(t)$	Total diversion from the river to demand site	50.39	49.33
$\sum Div_{ar}(t)$	Total diversion from the river to the artificial recharge area	42.94	29.00
$\sum R_d^g(t)$	Total groundwater pumping	96.17	106.00

target water table is more possible with the cyclic operation of the conjunctive use system. By looking at the results of Table 3, it can be seen that in the cyclic operation, the value of Q_{riv}^{out} (the surface water leaving the system's boundary) is about 29 MCM less than the non-cyclic approach, and a large volume of this water is used to recharge the aquifer. In addition, in the cyclic approach, less water is pumped from the aquifer, and the demand for surface water is higher than in the non-cyclic approach. Therefore, more artificial recharging and less groundwater extraction have caused the water table to be closer to the target level.

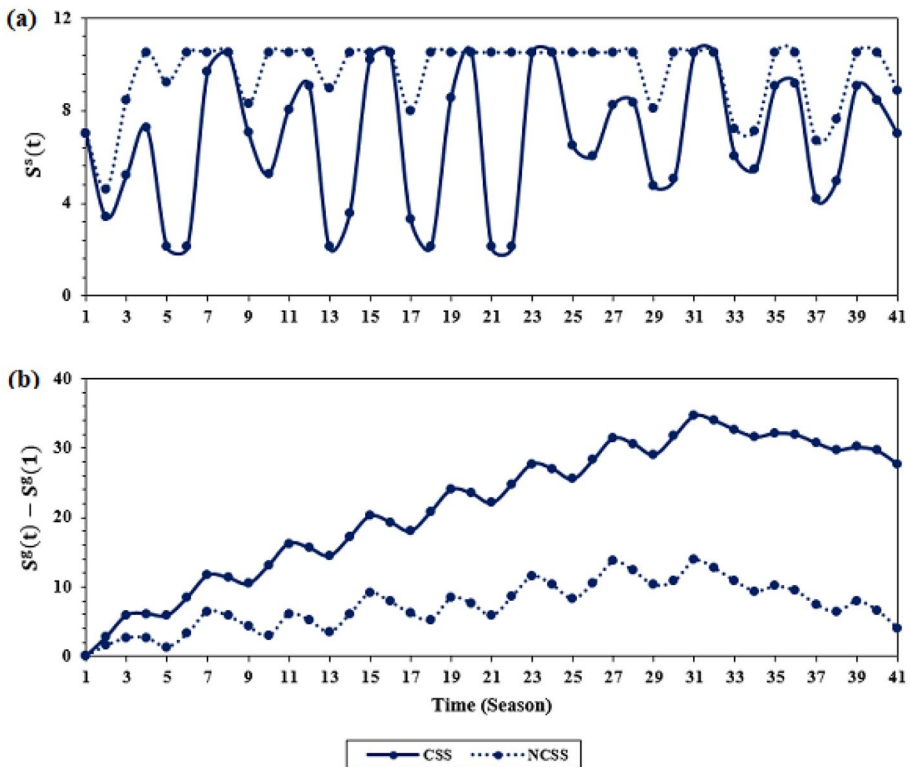


Fig. 5 Results for Pareto solutions ($SI = 0.585, DTWT = 712$) and ($SI = 0.585, DTWT = 1519$): (a) Surface reservoir storage and (b) Aquifer storage

In general, we believe that the CSS performs better than NCSS for two main reasons: More efficient water regulation through two storage tanks, namely 1- surface reservoir and 2- aquifer. In the conjunctive use systems that are operated with a cyclic strategy, the regulated water exchange between surface and groundwater reservoirs increases the empty volume of the surface reservoir, reduces spill and water loss, and causes more water to be stored in the aquifer in wet years/seasons for use in dry years/seasons (see Fig. 5). However, in NCSS, the direct recharge of aquifers is restricted to the wet years/seasons during the simulation period. This is probably why most of the time, the surface reservoir is full of water (see Fig. 5a), and this reduces the dam's capability to regulate river flow and increases water loss through overflow (spill). Furthermore, because river diversion subsystems have a known capacity, some water is directed to the artificial recharge and the demand sites. The rest of the water leaves the system's boundary. Hence, In the conjunctive use systems that are operated with a non-cyclic strategy, the sustainability of the demand areas and groundwater is threatened.

4 Conclusions

In this study, the adaptation of cyclic and non-cyclic conjunctive use of surface and groundwater strategies to climate change with the objectives of increasing groundwater sustainability and sustainability of water allocation to the agriculture sector were examined. The sustainability index was used in this study to evaluate water supply plans for future water availability in the agriculture sector, considering measures of reliability, resilience, vulnerability. Climate scenarios are derived from the Ensemble, CMCC-CMS, and MRI-CGCM3 global climate models, and the M5 decision tree algorithm is used to downscale the climatic data. It was intended to minimize deviation from target groundwater level while maximizing the sustainability index in delivering water to the agricultural sector. It was concluded that for any given sustainability index (SI), the total square deviations from target groundwater level (DTWT) with NCSS well exceeded that of the CSS operation strategy. It was shown that system performance with both CSS and NCSS would decline as addressed by decreased SI and increased DTWT for most of the scenarios and associated ensembles. It was observed that, achieving the target water table was more accessible with the cyclic operation of the conjunctive use system than NCSS. Cyclic water exchange between surface and groundwater reservoirs increased the empty volume of the surface reservoir, reduces spill and water loss, and caused more water to be stored in the aquifer in wet years/seasons for use in dry years/seasons.

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Authors' Contributions Abbas Afshar: Conceptualization, Methodology, Writing—original draft, Supervision, Funding acquisition. Mina Khosravi: Conceptualization, Methodology, Writing—original draft, Software. Amir molajou: Conceptualization, Methodology, Software.

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Declarations

Consent for Publication The authors give their full consent for the publication of this manuscript.

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