Joint Operation of Surface and Groundwater to Improve Sustainability Index as Irrigation System Performance: Cyclic Storage and Standard Conjunctive Use Strategies

Mina Khosravi[1]; Abbas Afshar[2]; Amir Molajou[3]; and Sam Sandoval-Solis, Ph.D., A.M.ASCE[4]

Abstract: A cyclic storage (CS) system is an extension to standard conjunctive use (SCU) of surface water (SW) and groundwater (GW) in which the SW bodies and GW aquifer(s) are treated as physically interconnected and operationally joint parallel storage facilities. Rule-based exchange of regulated water between surface reservoir(s) and GW aquifer(s) is the key element of a CS system that differentiates it from the SCU of SW and GW as usually practiced. This paper presents a novel multiobjective optimization model to develop a tradeoff between the sustainability index of water allocation to irrigated agriculture and energy required for GW pumping. The sustainability index, as defined in this paper, addresses reliability, vulnerability, and resilience. A solution to the large-scale multiperiod, multiobjective, mixed-integer nonlinear model was obtained using the ε-constraint method. The model maximizes the sustainability index while keeping the pumping energy at its minimum. Results show that CS operation strategy considerably improves the sustainability index compared to the SCU strategy. It is also shown how, for a given sustainability index, the required energy for pumping GW would decrease. Results may help decision-makers identify optimal policies and assess different policies under CS and SCU strategies. Agricultural-sector and system operators must become familiar with the predominance of CS over SCU for its real-world application. **DOI: 10.1061/(ASCE)WR.1943-5452.0001591.** *© 2022 American Society of Civil Engineers.*

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Introduction

The joint operation of groundwater (GW) and surface water (SW) has received increasing attention over the last decades (Bredehoeft and Young 1983; Coe 1990; Rezaei et al. 2017; Milan et al. 2018; Ticehurst and Curtis 2019; Jha et al. 2020; Chakraei et al. 2021). Conjunctive use of SW and GW may intend to harmoniously use both these resources to minimize the undesirable (and maximize the desirable) physical, social, environmental, and economic effects of their development (Fuchs et al. 2019; Zeinali et al. 2020). However, it is generally employed to pertain to any coordinated usage of SW and GW to meet water needs (Coe 1990). That is why conjunctive use often decreases uncertainties associated with SW supplies and plays a basic economic–hydrologic role in irrigation (Nayak et al. 2018; Paydar and Qureshi 2012; Liu and Chen 2020; Portoghese et al. 2021). This issue is especially significant in semiarid and arid areas where GW and SW resources are very valuable for economic development (Singh 2014; Sepahvand et al. 2019; Mirzaie et al. 2021).

Conjunctive water use may be categorized as short cycle–long cycle and active–passive (Dudley and Fulton 2006; Ostadrahimi 2013). Depending on the length of the recharge and recovery cycle, conjunctive use may be divided into two groups: short or long cycle. In an active conjunctive use program, SW is intentionally used to recharge an aquifer to secure a stable and reliable water source during drought periods (Singh 2014).

Conjunctive use models may be categorized as being lumped or distributed (Kerebih and Keshari 2021; Gong et al. 2020). In lumped models (black-box models), the modeling is mainly restricted to the water accounting and budgeting approach, and unlike distributed models, spatial variations of parameters are ignored. Distributed models may use either a fully distributed GW flow model (Willis and Liu 1984; Peralta et al. 1995) or GW response function such as a unit response matrix (URM) (Başağaoğlu et al. 1999; Alimohammadi et al. 2009; Seo et al. 2018).

Any conjunctive use scheme will benefit from direct or indirect recharge of aquifers. In common practice, the direct recharge of GWs is limited to wet periods during the planning horizon, which is referred to as the standard conjunctive use (SCU) approach in this research. In contrast, the cyclic storage (CS) system, as addressed hereafter, is a distinct extension to SCU of SW and GW in which the SW bodies and GW aquifer(s) are treated as physically interconnected and operationally joint parallel storage facilities (reservoirs). Rule-based exchange of regulated water between surface reservoir(s) and GW aquifer(s) is the key element of CS that differentiates it from the GW banking and SCU of SW and GW as usually practiced. Thomas (1978) first proposed the CS concept. Lettenmaier and Burges (1982) defined CS as: "the utilization of the GW resources as the nature storage and recovery facility, from which

[1]Ph.D. Candidate, Dept. of Civil Engineering, Iran Univ. of Science and Technology, Tehran 1684613114, Iran. Email: mina.khosravi100@gmail.com

[2]Professor, Dept. of Civil Engineering, Iran Univ. of Science and Technology, Tehran 1684613114, Iran (corresponding author). ORCID: https://orcid.org/0000-0001-8891-3426. Email: a_afshar@iust.ac.ir

[3]Ph.D. Candidate, Dept. of Civil Engineering, Iran Univ. of Science and Technology, Tehran 1684613114, Iran. Email: amolajou@yahoo.com

[4]Associate Professor, Dept. of Land, Air and Water Resources, Univ. of California, Davis, CA 95616. Email: samsandoval@ucdavis.edu

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water can be pumped in periods of low SW and to which surplus SW can be recharged. Such a system can be used in conjunction with a SW reservoir, which presents facilities for increasing the system reliability or, for the similar reliability, decreasing the surface storage development."

In SCU, however, uncontrolled spilled water from the reservoir or water leaving the watershed is often diverted for GW artificial recharge (Li and Gong 2002; Hashemi et al. 2015) and water loss from the watershed when the surface reservoir is full (Sekar and Randhir 2007). In fact, from the SCU perspective, use of regulated SW for GW artificial recharge does not seems economically viable. Therefore, artificial recharge through capturing floodwater may be the most feasible approach for managing GW resources (Dahan et al. 2008; Pavelic et al. 2012; Hashemi et al. 2015; MacEwan et al. 2017; Joodavi et al. 2020).

Joint operation of GW and SW subsystems under CS or SCU systems under different conditions is one of the significant issues in terms of saving energy, increasing supply reliability (Afshar et al. 2020), and enhancing sustainability of water allocation for irrigated agriculture. Earlier research on CS systems were mostly limited to the lumped modeling approach (Afshar et al. 2008) and single-objective semidistributed model (Alimohammadi et al. 2009; Afshar et al. 2010; Jahanpour et al. 2013) with different solution methodologies. In recent research, Afshar et al. (2020) introduced a generalized full-scale model for reliability-based optimum design of CS systems. Their reliability measure is restricted to the system performance measured by failure frequency in satisfying a prespecified agricultural demand. They disregarded the resilience (a measure of recovery from failure mode) and vulnerability (a measure of severity of any failure) of the system in their study. A thorough comparison of the conjunctive use of GW and SW systems with CS and SCU perspectives with sustainability measures including reliability, resilience, and vulnerability indices, which is the main focus of this paper, has not been tackled or reported yet.

This article presents a novel multiobjective optimization model to develop a tradeoff between the sustainability index of water allocation to irrigated agriculture and energy required for GW pumping. The most recent combination of reliability, vulnerability, and resilience is used to address the sustainability index. The model maximizes the sustainability index (SI) while keeping the pumping energy at a minimum. Performance of the proposed model is compared to that of well-established SCU of SW and GW resources. The proposed solution methodology employs the ε-constraint method to extract the Pareto fronts for CS and SCU operation strategies. A semidistributed GW model with the URM method is used to describe GW behavior and its interaction with SW bodies. Although we used the sustainability index and energy requirements as competing objective functions, many other objectives can be used without many changes in the model formulation and solution technique. The proposed modeling approach was applied to the Abhar River basin case example. It is shown that the approach is computationally feasible and practically sound, provided that the stakeholders appreciate its predominance over the SCU strategy.

Materials and Methods

Study Region and Basic Data

This case study included the Kinevars dam and Abhar River basin, which are in the Zanjan province of Iran (Fig. 1). The capacities of the various water transmission components and surface reservoir are shown in Table 1. GW is used conjunctively with SW for municipal water supply and agricultural purposes. GW is collectively managed in the irrigation area. Agriculture is the main user of SW and GW in the area. Seasonal environmental, municipal, and agriculture demands and the average seasonal inflow to the reservoir are presented in Table 2.

The GW aquifer consists of an 80-km^2 local aquifer and Kinevars dam, which regulates Abhar River flow. The aquifer has an impenetrable boundary except at the river outlet and inlet. The aquifer's spatial variation of the storage coefficients and hydraulic conductivity are shown in Fig. 1. Due to unrestricted GW pumping, the GW level has dropped approximately 10 meters in the last decade.

The longitudinal slope and Manning coefficient of Abhar River are considered to be 0.0001 and 0.02, respectively. Abhar River is divided into two reaches called the downstream and upstream reaches hereafter. The thickness of the semipervious stream bed layer is estimated at 3 m. Permeability coefficients of the semipervious stream bed layer for the upstream and downstream reaches are 7×10^{-6} m/s and 5×10^{-6} m/s, respectively.

Maximum seasonal GW extraction and recharge are restricted to 3 MCM. Maximum seasonal GW drawdown and rise are restricted to 10 m. These restrictions are intended to prevent GW overharvesting and reduce any associated problems.

To simplify the application, it is assumed that the discharge wells may equally be used as artificial recharge facilities. It is also considered that 10% of the supplied water and precipitation percolate into the aquifer (Alimohammadi et al. 2009).

Simulation Model

CS and SCU Systems

The surface reservoir (dam), aquifer, river, and demand site are the four main subsystems in the proposed CS and SCU approaches. The interrelation between the four subsystems is depicted in Fig. 2. Hydraulic exchange of water between the aquifer and river ($Q_{\mathrm{ar}}^{\mathrm{riv}}$), deep percolation of irrigation water (Deep), and that of precipitation infiltration (Seep) occur naturally. Table 3 provides a complete description of water transfer components. By specifying the operating policies of R_d^s, R_{ar}^s, R_{riv}^s, R_d^g, $\mathrm{Div}_d^{\mathrm{riv}}$, and $\mathrm{Div}_{\mathrm{ar}}^{\mathrm{riv}}$, the values of the other water transfer components (i.e., Spill and Ret) can be determined. Evaporation from the surface reservoir (E^s) and SW leaving the river's boundary ($Q_{\mathrm{riv}}^{\mathrm{out}}$) addresses the water leaving the system's boundary. Although $Q_{\mathrm{riv}}^{\mathrm{out}}$ may be recoverable by downstream users, E^s is considered irrecoverable for both CS and SCU approaches. Comparison of ($Q_{\mathrm{riv}}^{\mathrm{out}}$) in CS and SCU will reveal the merits of CS over the SCU approach. Seepage loss from the reservoir was reported as insignificant and was disregarded in this study.

In the SCU system, the regulated water is not applied for direct aquifer recharge, and the artificial recharge is restricted to the wet periods, when the water spills from the surface reservoir.

Modified Unit Response Matrix

As mentioned earlier, conjunctive use models may be simulated as lumped or distributed (Afshar et al. 2008). In lumped approaches, the spatial distribution of the aquifer response to stimuli at different locations is neglected, and the average response is usually considered the system response. One of the distribution modeling approaches of the GW system is to use an aquifer response function, such as the URM method. In this approach, the physical response function is extracted from a GW hydrologic model. The response function describes the GW response at various times and places as functions of various stimuli. The aquifer response is GW hydraulic head changes. The stimuli can occur in three states: (1) point stimuli

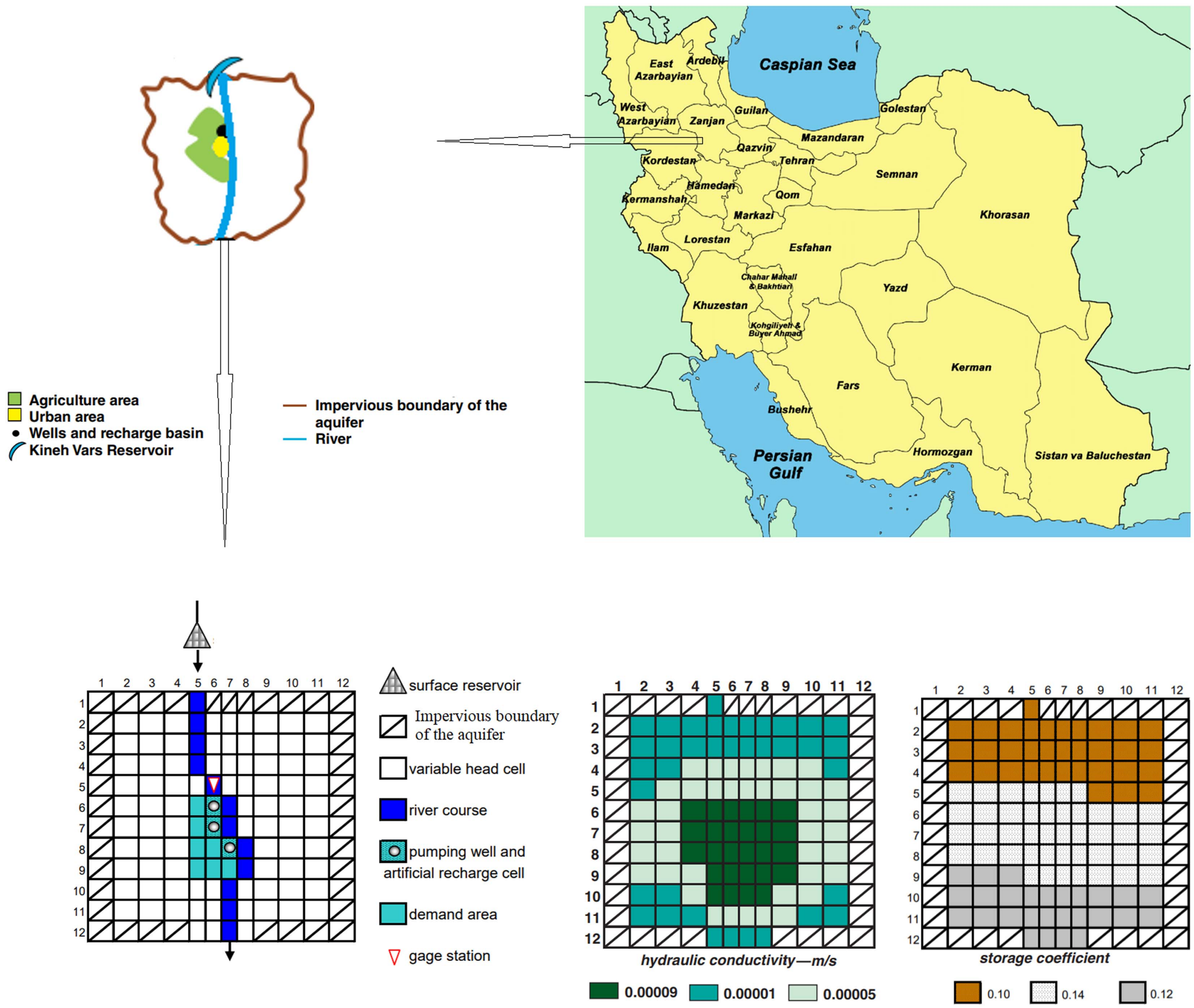

Fig. 1. Study area and aquifer hydraulic parameters.

Table 1. Capacities of the surface reservoir and water transfer components

Component	Capacity
Surface reservoir (dam)	10.5 MCM
Water transmission from the dam to the demand site	2.9 MCM/season
Water transmission from the dam to the artificial recharge site	0 MCM/season
Water transmission from the river to demand site	1.8 MCM/season
Water transmission from the river to the artificial recharge site	1.2 MCM/season

Table 2. Urban, agricultural, and environmental demands and average seasonal inflow to the reservoir (MCM)

Season	Urban	Agriculture	Environmental	Average inflows
Fall	2.056	0.834	0.262	4.825
Winter	1.464	0.000	0.262	9.116
Spring	2.850	8.169	0.542	16.693
Summer	4.030	6.597	0.542	0.936

(recharge or discharge wells), (2) linear stimuli (depth change of river), and (3) surface stimuli (deep percolation of precipitation or irrigation water).

Eq. (1) presents the equation of the URM method assuming point, linear, and surface stimuli (Morel-Seytoux 1975; Maddock 1972; Morel-Seytoux and Daly 1975)

$$s(i,n) = \sum_{t=1}^{n}\sum_{j=1}^{NP}\beta_P(i,j,n-t+1)\cdot P(j,t) + \sum_{t=1}^{n}\sum_{j=1}^{NL}\beta_L(i,j,n-t+1)\cdot L(j,t) + \sum_{t=1}^{n}\sum_{j=1}^{NS}\beta_S(i,j,n-t+1)\cdot S(j,t) \tag{1}$$

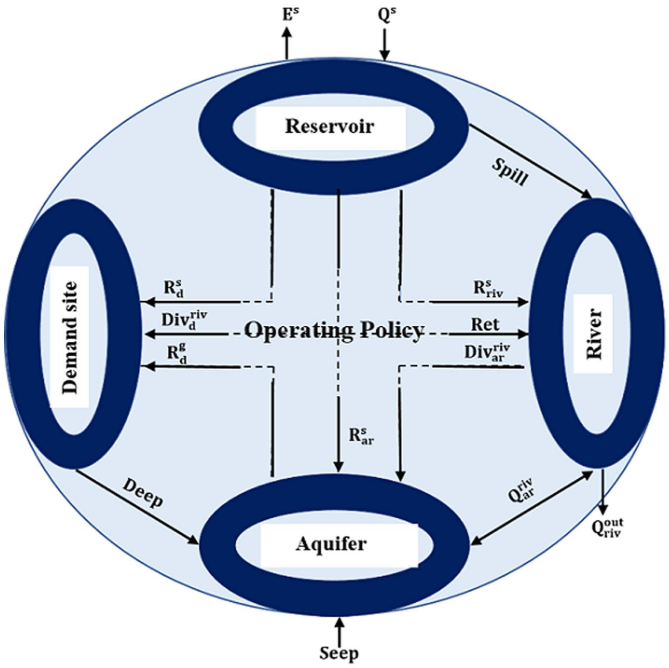

Fig. 2. Interrelation between the four subsystems in CS and SCU approaches.

Table 3. Description of water transfer components

Components	Description
R^s_d	Water transmission from the reservoir to the demand site
R^s_{riv}	Water release from the reservoir to the river
R^s_{ar}	Water transmission from the reservoir to the artificial recharge site
Spill	The spill from the dam
$\mathrm{Div}^{\mathrm{riv}}_d$	Water transmission from the river to demand site
$\mathrm{Div}^{\mathrm{riv}}_{\mathrm{ar}}$	Water transmission from the river to the artificial recharge site
R^g_d	GW pumping to demand site
Ret	Return water flows from the demand region to the river reaches

where $s(i,n)$ = GW hydraulic head change at node i at the end of time step n; $P(j,t)$, $L(j,t)$, and $S(j,t)$ = amount of point, linear, and surface stimuli at node j during time period t, respectively; $\beta_P(i,j,n-t+1)$, $\beta_L(i,j,n-t+1)$, and $\beta_S(i,j,n-t+1)$, or unit response coefficients for surface, linear, and point stimuli, respectively = change of the GW hydraulic head in node i at the end of time step n with unit point, linear, and surface stimuli at node j during time period t; NP, NL, and NS = total number of point, linear, and surface stimuli, respectively.

The URM is basically developed for a confined (artesian) aquifer. It may equally be used in unconfined (water table) aquifers if the GW drawdown is insignificant versus saturation layer depth. Otherwise, the original URM may be modified for application to unconfined aquifers. This paper benefits from the modified URM (MURM) as developed by Alimohammadi et al. (2009). Assuming point stimulation, Eq. (1) is modified to Eq. (2) as follows:

$$s(i,n) = \sum_{t=1}^{n} \sum_{j=1}^{\mathrm{NP}} m_P(i,j,n-t+1) \cdot \beta_P(i,j,n-t+1) \cdot P(j,t) \qquad (2)$$

where $m_P(i,j,n-t+1)$ = correction coefficient for stimulated node i for unit stimulation in exiting node j during time step t and may be presented as $m = (\frac{r}{u_r})/(\frac{e}{u_e})$, in which $\frac{r}{u_r}$ is the actual aquifer response to unit response and $\frac{e}{u_e}$ is the actual aquifer stimulation to unit excitation. According to Alimohammadi et al. (2009), the m_P is a correction parameter that partially sets the nonlinear response of the stimulated node in a water table aquifer.

The common method for generating unit response matrixes is to use a GW simulation model such as MODFLOW. First, the user must calibrate MODFLOW. Then, the simulation model must run repeatedly, each time only with a unit stimulation in the system and the required responses saved. To produce an element response matrix, responses of an individual with respect to all stimulations may be aggregated. Generating m-coefficients is similar to generating response coefficients. Again, the GW simulation model must run repeatedly with different values of excitations.

Formulation of CS and SCU Simulation Models

The integration of GW and SW simulation models as well as their interactions with each other and the demand site for CS and SCU approaches are presented in Appendix A.

Optimization Model

Sustainability Index

Sustainable development balances the conjunctive operation of SW and GW resources to meet water demand now and in the future (Schoups et al. 2006). To balance the water use and allocation from the two sources, one may use appropriate indices as credible measures for comparison and evaluation of SW and GW systems performances under various scenarios. Sandoval-Solis et al. (2011) suggested the following SI to quantify the sustainability of water resources systems:

$$\mathrm{SI} = [\mathrm{Rel} \times \mathrm{Res} \times (1 - \mathrm{Vul})]^{1/3} \qquad (3)$$

where Rel, Res, and Vul = reliability, resilience, and vulnerability performance measures, respectively. The deficit has widely been used to address reliability, resilience, and vulnerability in water resources management (Sandoval-Solis et al. 2011).

Reliability is obtained by dividing the number of satisfactory (NOS) periods (i.e., zero deficit) by the number of total time periods (NT) (McMahon et al. 2006)

$$\mathrm{Rel} = \frac{\mathrm{NOS}}{\mathrm{NT}} \qquad (4)$$

Resilience is the probability that a successful time period (the demand is fully supplied) will follow a failure period (NSF) for all failure periods (NOF). This criterion evaluates the recovery of the system once it has failed (Sandoval-Solis et al. 2011)

$$\mathrm{Res} = \frac{\mathrm{NSF}}{\mathrm{NOF}} \qquad (5)$$

Vulnerability is defined as the ratio of average annual deficit with respect to the annual water demand (ANDM)

$$\mathrm{Vul} = \frac{\sum_{t=1}^{\mathrm{NT}} \mathrm{Def}(t)/\mathrm{NOF}}{\mathrm{ANDM}} \qquad (6)$$

Formulation of CS and SCU Optimization Models

This part provides a mixed-integer, multiperiod, nonlinear, multiobjective CS and SCU optimization models with the pumping energy requirement and sustainability index as conflicting objectives.

Water transfer between different subsystems [including $R_d^s(t)$, $Div_d^{\mathrm{riv}}(t)$, $R_d^g(t)$, $Div_{ar}^{\mathrm{riv}}(t)$, $R_{\mathrm{riv}}^s(t)$, and $R_{\mathrm{ar}}^s(t)$] are identified as decision variables of the proposed biobjective optimization models. The mathematical formulation of the model can be found in Appendix B.

ε-Constraint Method

In the ε-constraint method, one of the objective functions is optimized while treating the others as additional constraints in the optimization model. For the CS and SCU optimization models, the required pumping energy is introduced as the main objective function that should be minimized, and the SI is added to the set of constraints as Eq. (7). In Eq. (7), by changing the values of ε, the set of optimal solutions known as Pareto solutions is obtained

$$\mathrm{SI} \geq \varepsilon \tag{7}$$

Results

CS and SCU Systems Results

CS and SCU optimization models were run for different ε values. Fig. 3 indicates the Pareto front of the sustainability index (which is dimensionless) and pumping energy (PE, which is in joules). As illustrated in Fig. 3, the CS strategy performed much better than SCU when the desired sustainability index exceeded 0.6, where the required pumping energy was greater than 10 (10^{12} J). For a lower desired sustainability index, however, both approaches resulted in relatively similar pumping energy. In fact, for a sustainability index below 0.6, GW extraction in the CS and SCU modeling scheme was very similar, which resulted in very close performance of both approaches. Restricting energy use to zero, the sustainability index for CS and SCU operational strategies dropped to 0.42 to 0.40, respectively. Although for some levels of pumping energy (i.e., $6 < \mathrm{PE} < 12$), the sustainability index for the proposed two models did not vary significantly, the CS system outperformed the SCU system over the entire feasible solution space. As the sustainability index approached 1, the CS system performed much better than the SCU system. No matter how much energy was used, the sustainability index in SCU never exceeded 0.697. Employing the CS strategy, on the other hand, was capable of improving the sustainability index to almost 0.80 for the same level of energy consumption. The figure shows that the sustainability index with the proposed CS system may reach a maximum value of 0.856 if the energy use is allowed to increase to almost 26 (10^{12} J) over the entire operational horizon (40 seasons).

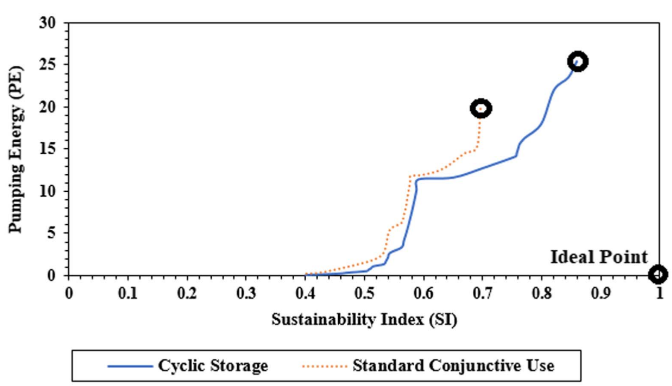

Fig. 3. Pareto front of sustainability index-pumping energy (10^{12} J) in CS and SCU strategies.

For detailed comparison and discussion of the performances of CS and SCU, two solutions, marked with circles, from the Pareto front are selected: (1) CS solution (Rel = 0.875, Res = 0.800, Vul = 0.103, SI = 0.86); and (2) SCU solution (Rel = 0.650, Res = 0.643, Vul = 0.189, SI = 0.70). These solutions address the alternatives with the maximum sustainability index for the CS and SCU operational strategies. As it turns out, the CS strategy improved system performance by increasing reliability and reversibility and reducing vulnerability. To be informative, the discussion focuses on three different subsystems: SW, GW, and water use subsystems. In the following sections, the amounts of transmission from different components are in MCM.

Comparison of CS and SCU Results for Maximum Sustainabilities

SW Subsystem

The time variation of reservoir storage $[S^s(t)]$ and changes in reservoir storage $[\Delta S^s(t)]$ for CS and SCU systems are presented in Fig. 4. As shown in Table 2, the historical inflow to the reservoir reveals that more than 52% of the total inflow occurred in spring seasons (as wet seasons) over the 10 years of simulation. On the other side, the total inflow in the summer seasons (as dry seasons) was less than 3% of the total runoff. Therefore, due to high demand in summer, for most summer seasons, the inflow to the reservoir was smaller than the release, and the diagrams of $\Delta S^s(t)$ for the CS and SCU systems show negative values. In other words, in both models, the surface reservoir regulated the inflow to the reservoir during the wet seasons for use during the dry seasons with greater demand. However, the sum of these negative values for CS operation exceeded that of SCU by 25 MCM over the entire operation period (−69.2 compared to −44.1 MCM).

Some interesting conclusions can be drawn from detailed observation of the results, as presented in Fig. 4. As expected, the SCU system ended up with a more frequent full reservoir compared to the CS system. In fact, the number of seasons with a full reservoir were 5 and 23 for the CS and SCU systems, respectively. This in turn, reduced the volume of uncontrolled spill over the entire simulation horizon. Allowing artificial recharge from the regulated water (CS operation) resulted in significantly higher variation in changes of reservoir storage $[\Delta S^s(t)]$ from one season to another.

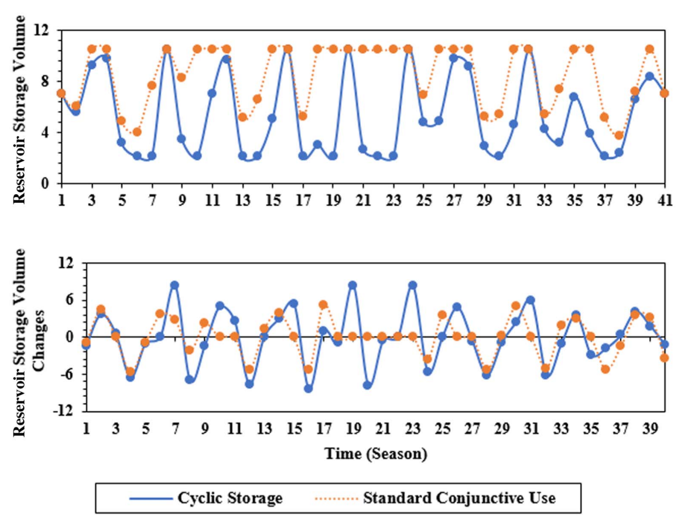

Fig. 4. Volumes of reservoir storage $[S^s(t)]$ and reservoir storage changes $[\Delta S^s(t)]$ in CS and SCU strategies.

It is interesting to observe that the total volume of stored water over the entire simulation horizon for SCU and CS systems was 349 and 219.8 MCM, respectively. By using regulated water for artificial recharge, the CS system stored 129.2 MCM less water compared to the SCU system. Although not addressed in this study, this difference in stored water may reduce evaporation losses and be further used for flood control purposes.

Water Use Subsystem

Fig. 5 shows the time variation of water deficit and water supply from different components of the system as addressed by supply through the aquifer (R_d^g), surface reservoir (R_d^s), and direct offtake from the river ($\mathrm{Div}_d^{\mathrm{riv}}$) in CS and SCU systems. Given this figure, the trend of water supply was almost repeated intermittently in the first 8 years for the CS system. As presented, water transfer through SW components during the high-demand seasons, addressed by supply from the reservoir (R_d^s) and direct offtake from the river ($\mathrm{Div}_d^{\mathrm{riv}}$), was at a maximum capacity of 2.9 and 1.8 MCM per season. During these periods, SW relieved the highest priority limited by capacity restriction. GW was pumped to supplement the SW as needed. Most of the total deficit occurred in the last 2 years, where inflow to the reservoir was at its minimum. As observed, during the last 2 years, water supply through SW was minimal, asking for higher GW pumping, if possible. Nonetheless, a significant deficit during the last few seasons was inevitable.

The results of the SCU strategy (Fig. 5) presented no well-established pattern for supplies from different sources. This strategy followed the standard operating policy (SOP) in the operation of SW, with a secondary role given to the GW supply. Therefore, considering the GW storage and head limitations, a deficit was inevitable if the sum of limited SW and GW could not fully satisfy the demand. This situation was quite severe during the last 10 seasons; where GW level (storage) was at its minimum, very little could be pumped. Hence, very large deficits were observed.

The values of water leaving the system for SCU operation exceeded that of CS operation by 25 MCM over the entire operation period (162.5 compared to 137.5 MCM). Therefore, by employing CS operation, this water can be put in the aquifer, which would reduce the pumping head, increase potential pumping volume, and reduce the time when GW cannot be pumped. This implies greater management and control over SW in the CS system rather than SCU. Therefore, the CS strategy has the potential to be a solid foundation for a successful water resources management plan.

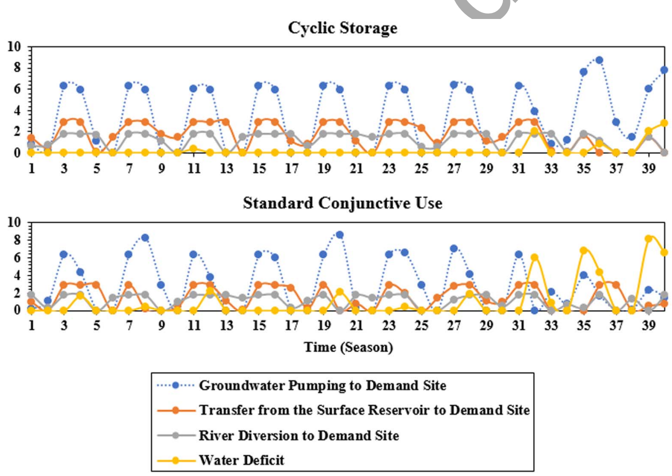

Fig. 5. Deficit and supply graphs by various components in CS and SCU strategies.

GW Subsystem

One of the major differences between the two strategies (CS and SCU) is the contribution and values of aquifer storage over the operational time horizon. The time variation of the aquifer storage of the selected solutions for CS and SCU strategies is presented in Fig. 6. As shown, unlike the SCU strategy, the aquifer storage for CS strategy was always greater than its initial storage. The main reason for this can be seen in Fig. 7. As illustrated, in the CS approach, SW was diverted for artificial recharge of the aquifer with its full capacity during the wet years (first 8 years), even if the reservoir was not full. In other words, the system kept recharging the aquifer to keep storage high enough for the upcoming dry years. This is a distinct value to the CS operational strategy. As illustrated (Fig. 7), previously stored water in the aquifer was used to keep the deficit at its possible minimum during the last 2 dry years. This is why the average aquifer storage increased in the wet years, and it suddenly went down in the dry years, whereas in SCU operation, the aquifer was only recharged in seasons when the water spilled from the surface reservoir.

In CS operation, the discharge from the aquifer in spring and summer seasons was greater than recharge, and it was due to the high water demand in these seasons. For this reason, the local largest and smallest values of aquifer storage volume happened in the spring and fall seasons, respectively. Therefore, the volume of aquifer storage increased in the first half of each year and decreased in the second half of the same year.

Based on the previous content, it can be concluded that in the CS system, water is accumulated in the aquifer in wet times for application during dry times. Thus, with greater water management and control, the sustainability of water allocation increases. Also, the increase in energy consumption in the CS approach is due to the increase in GW discharge, not due to the decrease in aquifer level. Therefore, for any given sustainability index, the energy consumption in the CS approach will be reduced by keeping the aquifer level high.

To confirm the results obtained in previous sections, the results for CS and SCU Pareto solutions (PE $= 15.3 \times 10^{12}$ J, SI $= 0.76$,

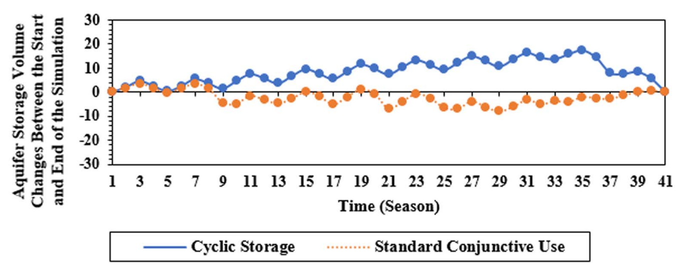

Fig. 6. Aquifer storage volume changes $[S^g(t) - S^g(1)]$ in CS and SCU strategies.

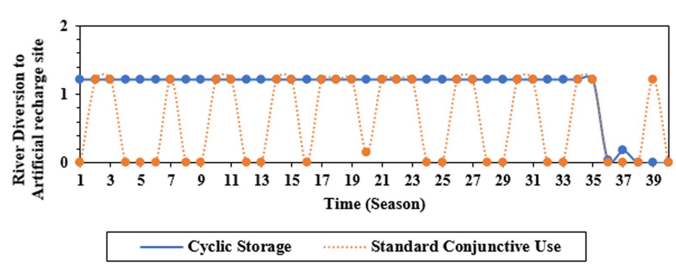

Fig. 7. River diversion values to the artificial recharge site in CS and SCU strategies.

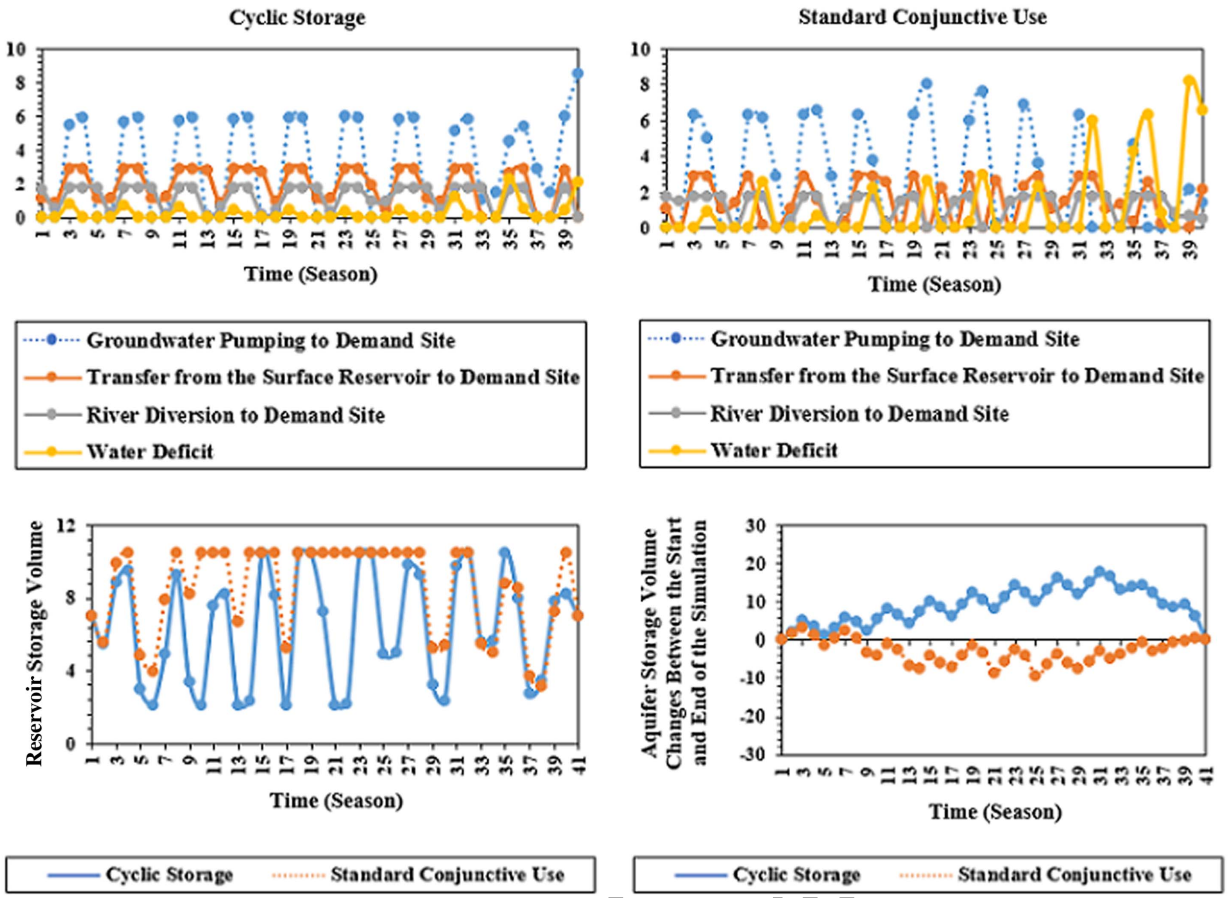

Fig. 8. Results for Pareto solutions (PE = 15.3×10^{12} J, SI = 0.76) and (PE = 15.3×10^{12} J, $SI = 0.69$) in CS and SCU strategies.

Rel = 0.675, Res = 0.692, Vul = 0.053) and (PE = 15.3×10^{12} J, SI = 0.69, Rel = 0.650, Res = 0.643, Vul = 0.214) are also shown in Fig. 8. The energy consumed in these Pareto solutions is the same, but the sustainability index in the CS Pareto solution is 50% more than that for the SCU Pareto solution. Looking closely at the graphs in Fig. 8, it appears that all the arguments presented in previous sections are true in justifying the superiority of the CS approach over the SCU approach. The most important of these arguments are: (1) in the CS system, the surface reservoir regulates more inflow during the wet seasons for use during the dry seasons with greater demands, and (2) in the CS approach, the drought reserve capacity in the GW is much higher than in the SCU approach. In general, the greater management of SW and GW in CS rather than SCU operation causes the sustainability index to increase from 0.69 to 0.76, respectively.

Long-Term Cycle Operation Model

In previous sections, the results of the CS and SCU operation models were presented for a period of 40 seasons (short-term models). The results showed that the CS system outperformed the SCU system if the sustainability index and energy consumption for GW pumping were the objectives. The validity and extent of this observation may be reinforced by applying the models to a longer period.

In order to validate these results, the CS operation model was applied to a 120-season problem. The data for the long-term model covers 1988–2018. The data for the long-term and short-term models have an overlap during 2008–2018 (Table 2). Fig. 9 presents the seasonal deficit, diversion for demand site, and water supplied through the surface reservoir and aquifer. As illustrated, the deficit over the entire simulation period (120 seasons) is 0, leading to a sustainability index of 1. To justify this finding, we shall focus on the results of the last 40 seasons of the long-term model. Time variation of the GW storage for the last 40 seasons of the long-term and short-term models is presented in Fig. 10. As illustrated, the short-term model assumed an initial storage for GW and tended to end up with the same storage at the end of the operation period, whereas the long-term model assumed the same storage at the beginning of the simulation, which went back to 1988 (compared to 2008 in the short-term model). Therefore, as shown, the system managed to have an additional 12 MCM GW storage available in 2008 to start with (Fig. 10). This additional GW storage was used to overcome the potential water shortage in the last 2 dry years.

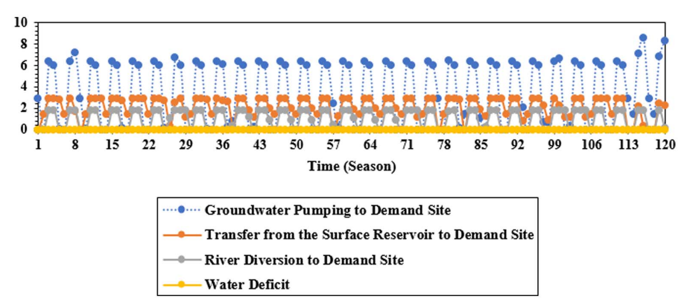

Fig. 9. Deficit and water supply values by various components in long-term CS strategy model.

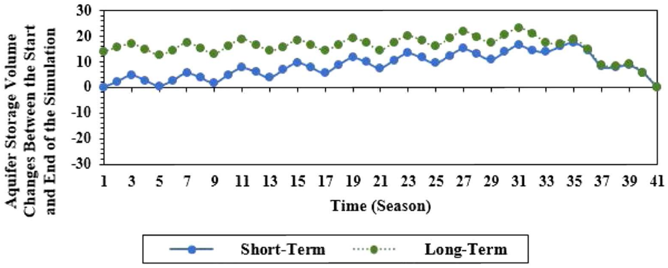

Fig. 10. Aquifer storage volume changes $[S^g(t) - S^g(1)]$ in short-term CS operation model and the last 40 seasons of long-term CS operation.

Conclusions

In this study, CS and SCU operational strategies for conjunctive use of SW and GW were compared using a biobjective optimization model for maximizing sustainable water delivery to the agricultural area and minimizing energy consumption. The application of the proposed CS and SCU strategies revealed that CS may significantly increase the sustainability index under any level of energy use. In the SCU system, the sustainability of water resource systems is severely reduced by neglecting the potential of GW. The CS strategy provides a good balance between the recharge and discharge of GW storage to fulfill the demand to enhance sustainability. It was shown that the amount of water leaving the system in the CS system is significantly smaller than that of SCU. It was shown that, for the same reservoir capacity, the CS strategy ends up with relatively more empty space compared to the SCU. This available empty space in the reservoir may be used for flood control, if planned. The inclusion of flood control in the reservoir operation with CS and SCU strategies was not considered in this study and could be a subject for further study.

It is clear that implementing a CS approach in the real world faces challenges and requires deeper consideration. Operators and stakeholders must first accept that the CS strategy optimizes system performance in the long-term planning horizon. In this regard, they must be educated. Then, conflicts between different stakeholders, including farmers, SW managers, GW managers, and operators, must be identified and resolved. This issue can be considered by future researchers.

Appendix I. Formulation of CS and SCU Simulation Models

CS System Simulation Models

Surface Reservoir Simulation Model

$$S^s(t+1) = S^s(t) + \Delta S^s(t) \tag{8}$$

$$\Delta S^s(t) = Q^s(t) - E^s(t) - R^s_d(t) - R^s_{\mathrm{ar}}(t) - R^s_{\mathrm{riv}}(t) - \mathrm{Spill}(t); \quad \forall t \tag{9}$$

$$\Delta S^s_2(t) = Q^s(t) - E^s(t) - R^s_d(t) - R^s_{\mathrm{ar}}(t) - R^s_{\mathrm{riv}}(t); \quad \forall t \tag{10}$$

$$\mathrm{Storage}\ (t) = S^s(t) + \Delta S^s_2(t); \quad \forall t \tag{11}$$

$$\mathrm{Spill}(t) = \begin{cases} \mathrm{Storage}\ (t) - \mathrm{CapD} & \text{if } \mathrm{Storage}\ (t) > \mathrm{CapD}; \forall t \\ 0 & \text{if } \mathrm{Storage}\ (t) \le \mathrm{CapD}; \forall t \end{cases} \tag{12}$$

$$A^s(t) = a_0 + a_1 S^s(t); \quad \forall t \tag{13}$$

$$E^s(t) = \mathrm{ep}(t) \cdot (A^s(t) + A^s(t+1))/2; \quad \forall t \tag{14}$$

where $S^s(t)$ = storage volume of the dam; $\Delta S^s(t)$ = dam storage volume changes; $\Delta S^s_2(t)$ = changes in reservoir storage volume within the reservoir active storage; Storage (t) = water inventory of surface reservoir before overflow, $A^s(t)$ = reservoir surface area corresponding to $S^s(t)$; CapD = capacity of the dam, ep(t) = evaporation height; and a_0 and a_1 = fixed coefficients. Eq. (12) shows that this model is resolved without any forward-looking flood control logic.

Demand Site Water Volume Balance

$$\mathrm{Sup}(t) = R^s_d(t) + R^g_d(t) + \mathrm{Div}^{\mathrm{riv}}_d(t); \quad \forall t \tag{15}$$

$$\mathrm{Dem}(t) = \mathrm{Sup}(t) + \mathrm{Def}(t); \quad \forall t \tag{16}$$

$$\mathrm{Dem}(t) = \mathrm{DemAgri}(t) + \mathrm{DemUrb}(t); \quad \forall t \tag{17}$$

where Def(t) = water deficit in the agriculture sector; Dem(t) and Sup(t) = Demand(t) and Supply(t), respectively; DemAgri(t) and DemUrb(t) = agricultural and urban water demand at time step t, respectively.

Aquifer Water Volume Balance

$$S^g(t+1) = S^g(t) + \Delta S^g(t); \quad \forall t \tag{18}$$

$$\Delta S^g(t) = \sum_{w=1}^{\mathrm{NAR}} q_{\mathrm{ar}}(w,t) - \sum_{w=1}^{\mathrm{NW}} q_p(w,t) + \sum_{r=1}^{\mathrm{NR}} kqv(t) \cdot Q^{\mathrm{riv}}_{\mathrm{ar}}(r,t) + \mathrm{Deep} \cdot \mathrm{Sup}(t) + \mathrm{Prc}(t) \cdot \mathrm{Seep} \cdot \mathrm{AQA}; \quad \forall t \tag{19}$$

$$\sum_{w=1}^{\mathrm{NW}} q_p(w,t) = R^g_d(t); \quad \forall t \tag{20}$$

$$\sum_{w=1}^{\mathrm{NAR}} q_{\mathrm{ar}}(w,t) = R^s_{\mathrm{ar}}(t) + \mathrm{Div}^{\mathrm{riv}}_{\mathrm{ar}}(t); \quad \forall t \tag{21}$$

where $S^g(t)$ = storage volume of the aquifer; $\Delta S^g(t)$ = aquifer storage volume changes; $q_p(w,t)$ and $q_{\mathrm{ar}}(w,t)$ = volume of discharge from and recharge to the well w, respectively; kqv(t) = conversion factor (discharge to volume) in time step t; AQA = aquifer surface area; and Prc = precipitation depth. These equations are only used to estimate the volumetric changes in the aquifer due to pumping or recharging from the wells and all linear and surface interactions.

GW Simulation Model

$$s(i,n) = \sum_{t=1}^{n}\sum_{j=1}^{\mathrm{NP}} m_p(i,j,n-t+1) \cdot \beta_p(i,j,n-t+1) \cdot q_p(j,t) + \sum_{t=1}^{n}\sum_{j=1}^{\mathrm{NAR}} m_{\mathrm{ar}}(i,j,n-t+1) \cdot \beta_{\mathrm{ar}}(i,j,n-t+1) \cdot q_{\mathrm{ar}}(j,t) + \sum_{t=1}^{n}\sum_{j=1}^{\mathrm{NR}} m_{\mathrm{riv}}(i,j,n-t+1) \cdot \beta_{\mathrm{riv}}(i,j,n-t+1) \cdot \mathrm{dh}_{\mathrm{riv}}(j,t) + \sum_{t=1}^{n}\sum_{j=1}^{\mathrm{NS}} m_S(i,j,n-t+1) \cdot \beta_S(i,j,n-t+1) \cdot P_S(j,t) \tag{22}$$

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where $s(i,n)$ = hydraulic head change in node i at the end of time period n due to the point, linear, and surface stimuli at all nodes j during time period t; for example, $s(w,n)$ and $s_{\text{riv}}(r,n)$ are GW hydraulic head change in well w and river reach r at the end of time period n, respectively; p, ar, riv, and a = indices of pumping wells, artificial recharge wells, river reaches, and surface stimuli (i.e., precipitation and irrigation), respectively; NP, NAR, NR, and NS = total number of pumping wells, artificial recharge wells, river reaches, and surface stimuli, respectively.

River–Aquifer Interactions Simulation Model

$$Q_{\text{ar}}^{\text{riv}}(r,t) = \text{Criv}(r)\cdot(h_{\text{riv}}^{s}(r,t) - h_{\text{riv}}^{g}(r,t)) \quad \text{if } h_{\text{riv}}^{g}(r,t) > h_{\text{riv}}^{\text{bot}}(r); \quad \forall r,t \tag{23}$$

$$Q_{\text{ar}}^{\text{riv}}(r,t) = \text{Criv}(r)\cdot(h_{\text{riv}}^{s}(r,t) - h_{\text{riv}}^{\text{bot}}(r)) \quad \text{if } h_{\text{riv}}^{g}(r,t) \le h_{\text{riv}}^{\text{bot}}(r); \quad \forall r,t \tag{24}$$

$$\text{Criv}(r) = K(r)\cdot L(r)\cdot W(r)/M(r); \quad \forall r \tag{25}$$

$$h_{\text{riv}}^{g}(r,t) = h_{\text{riv}}^{g}(r,0) - s_{\text{riv}}(r,t); \quad \forall r,t \tag{26}$$

$$h_{\text{riv}}^{s}(r,t) = h_{\text{riv}}^{\text{bot}}(r) + M(r) + h_{\text{riv}}(r,t); \quad \forall r,t \tag{27}$$

where $K(r)$, $M(r)$, $L(r)$, and $W(r)$= hydraulic conductivity, thickness, length, and width of the semipervious streambed in the river reach r, respectively; $\text{Criv}(r)$ = hydraulic conductance of the aquifer–stream interconnection; $h_{\text{riv}}^{s}(r,t)$ = hydraulic head in the river reach r; $h_{\text{riv}}^{\text{bot}}(r)$ and $h_{\text{riv}}^{g}(r,t)$= elevation of the semipervious streambed bottom and GW hydraulic head below the river reach r, respectively; $s_{\text{riv}}(r,t)$ = aquifer water table drawdown; $h_{\text{riv}}(r,t)$ = river water depth in reach r in period t; and $h_{\text{riv}}^{g}(r,0)$ = initial elevation.

River Hydraulics Simulation Model

$$\Delta S_{\text{riv}}(r,t) = (Q_{\text{riv}}^{\text{in}}(r,t) + ql_{\text{riv}}(r,t) - Q_{\text{riv}}^{\text{out}}(r,t))\cdot kqv(t); \quad \forall r,t \tag{28}$$

$$ql_{\text{riv}}(r,t) = \frac{\text{Area}(r)\cdot\text{Prc}(t) - \text{Div}_{d}^{\text{riv}}(t) - \text{Div}_{\text{ar}}^{\text{riv}}(t) + \text{Retr}(r)\cdot\text{Sup}(t)}{kqv(t)} + Q_{\text{ar}}^{\text{riv}}(t); \quad \forall r,t \tag{29}$$

$$Q_{\text{riv}}^{\text{in}}(1,t) = (R_{\text{riv}}^{s}(t) + \text{Spill}(t))/kqv(t); \quad \forall t \tag{30}$$

$$Q_{\text{riv}}^{\text{in}}(r+1,t) = Q_{\text{riv}}^{\text{out}}(r,t); \quad \forall r,t \tag{31}$$

$$Q_{\text{riv}}^{\text{in}}(r,t) = f_4(h_{\text{riv}}(r,t)); \quad \forall r,t \tag{32}$$

$$Q_{\text{riv}}^{\text{out}}(r,t) = f_5(h_{\text{riv}}(r,t)); \quad \forall r,t \tag{33}$$

$$\Delta S_{\text{riv}}(r,t) = \text{Area}(r)\cdot dh_{\text{riv}}(r,t); \quad \forall r,t \tag{34}$$

where $\Delta S_{\text{riv}}(r,t)$ = river storage volume changes; $Q_{\text{riv}}^{\text{in}}(r,t)$ = river inflow to the river reach r; $ql_{\text{riv}}(r,t)$ = lateral inflows and outflows along the river reach r; $h_{\text{riv}}(r,t)$ = river depth in reach r in time step t; and $\text{Area}(r)$ = river surface area.

SCU System Simulation Models

CS and SCU systems have common simulation models. According to the concepts presented in the previous sections, in the SCU approach, the term $R_{\text{ar}}^{s}(t)$ should be removed from the volume balance equation of the surface reservoir

$$R_{\text{ar}}^{s}(t) = 0; \quad \forall t \tag{35}$$

Appendix II. Formulation of Optimization CS and SCU Models

CS System Optimization Model

Objective Functions

$$\text{Minimize PE} = \sum_{t=1}^{\text{NT}}\sum_{w=1}^{\text{NW}} f_1(q_p(w,t), s(w,t)) \tag{36}$$

$$f_1(q_p(w,t), s(w,t)) = \gamma\cdot\left(\frac{\sum_{w=1}^{\text{NW}} q_p(w,t)}{kqv(t)}\right)\cdot\left(l_w + \left(\frac{s(w,t)+s(w,t-1)}{2}\right)\right)\cdot\Delta t \tag{37}$$

$$\text{Maximize SI} = [\text{Rel}\times\text{Res}\times(1-\text{Vul})]^{1/3} \tag{38}$$

where l_w = initial drop in wells; NT = number of time period t; and γ = specific gravity of water. The system is subject to various physical and operational constraints, as partially addressed by the following equation.

Capacity Constraints

$$S^{s}(\text{NT}+1) \ge S^{s}(1) \tag{39}$$

$$S^{s}(t) \le \text{CapD}; \quad \forall t \tag{40}$$

$$R_{j}^{i}(t) \le \text{Cap}^{i} \tag{41}$$

where $R_{j}^{i}(t)$ = water transfer from subsystem i to subsystem j at time period t; and Cap^{i} = capacity of water transfer component i.

Constraints on Demand Site

$$\text{def}(t) \le \text{DemAgri}(t); \quad \forall t \tag{42}$$

Using Eq. (42), the urban water need will be completely satisfied, and only the agricultural sector will suffer from water deficits.

Constraints on Aquifer

$$S^{g}(\text{NT}+1) \ge S^{g}(1) \tag{43}$$

$$q_p(w,t) \le q_p^{\max}; \quad \forall w,t \tag{44}$$

$$q_{\text{ar}}(w,t) \le q_{\text{ar}}^{\max}; \quad \forall w,t \tag{45}$$

$$s^{\min} \le s(w,t) \le s^{\max}; \quad \forall w,t \tag{46}$$

where $q_p^{\max}$ and $q_{\text{ar}}^{\max}$ = maximum GW extraction and recharge rates, respectively; and $s^{\min}$ and $s^{\max}$ = minimum and maximum water table change per well.

Constraints on River Hydraulics

$$Q_{\text{riv}}^{\min}(r,t) \leq Q_{\text{riv}}^{\text{out}}(r,t) \leq Q_{\text{riv}}^{\max}(r,t); \quad \forall r,t \tag{47}$$

where $Q_{\text{riv}}^{\max}$ and $Q_{\text{riv}}^{\min}$ = maximum river capacity and minimum environmental requirement, respectively.

SCU System Optimization Model

By adding the constraints in Eqs. (48) and (49) to the CS optimization model, the SCU optimization model is obtained

$$R_{\text{riv}}^{s}(t) \leq \text{Div}_{d}^{\text{riv}}(t) + \text{CapEn}(t); \quad \forall t \tag{48}$$

$$\text{Div}_{\text{ar}}^{\text{riv}}(t) \leq \text{Spill}(t); \quad \forall t \tag{49}$$

where $\text{CapEn}(t)$ = environmental demand at the time period t. In the SCU operation strategy, the release from the dam occurs to meet the downstream municipal, environmental, and irrigation water demand [Eq. (48)], and the artificial recharge is applied only in periods of spill [Eq. (49)].

Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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