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Increasing Agricultural Resilience through Combined Supply and Demand Management (Case Study: Karaj Reservoir Dam, Iran)

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Abstract: Among the solutions to climate change's harmful effects, AS (Adaptation Strategies) are more feasible. In this study, four AS, Changing Cultivation Dates (CCD), Deficit Irrigation (DI), Improving Irrigation Performance (IIP), and Optimizing the Crop Pattern (OCP), were investigated. The results showed that the WUE (Water Use Efficiency) was declined when the cultivation date was changed for all crops in the baseline and increased after the cultivation date was brought forward to 7, 14, 14, 28, 28 days for tomato, wheat, corn, barley and cucumber, respectively, in the future period. Deficit irrigation of 30% increased the WUE in all crops. A 48% increase in irrigation performance reduced demand by 10%. Following the OCP and diminishing the cultivation area by 30% increased farmers' total profit and reduced the water consumption volume by 9% and 11%, respectively, in the baseline and future periods. To study the effect of these AS on crop yield and allocated volume, a combination of crop model programming and the MOEPO (Multi-Objective Emperor Penguin Optimizer) was employed to minimize Vulnerability and maximize Reliability Indexes (Performance Indexes). In the supply section, three scenarios were examined. The results showed that DI, IIP, CCD and OCP were classified from the most to the least option based on improving the Performance Indexes.

Keywords: deficit irrigation; irrigation performance; cultivation date; crop pattern; adaptation strategies; agricultural resilience; multi-objective optimization

1. Introduction

Global warming and climate change are important topics that have been studied by researchers around the world in recent decades [1]. In the Karaj (Iran) basin, various studies on climate change have shown that the average annual temperature and precipitation will have significant upward and downward trends, respectively [2,3]. Comprehensive research on water consumption has shown that a balance between resources and consumption can only be achieved if the performance of the agricultural sector increases [4–6]. As a result, it is necessary to simultaneously identify the effects of climate change on the irrigation system at the basin level in both the consumption and resource sections. To increase the resilience of water projects, Adaptive Strategies (AS) are proposed, which have not been given enough attention so far.

This study aimed to increase the resilience of the Karaj Dam reservoir in supplying water demand to agricultural sections against the effects of climate change. Operational policies that increase reliability and reduce the vulnerability of the water resources system can help to increase its resilience [7]. In this regard, this study tried to provide a comprehensive hybrid model of decision support, a model that can estimate the effects of climate change, temperature, precipitation, available water and demands of the basin with reasonable certainty and manage water supply and demands to increase the WUE, reduce consumed water, and minimize reservoir deficits.

The complexity of the relationship, similar to this study's issues, the time constraints, and the spread of technology, has led scientific studies to be directed to methods that, while increasing speed and using minimal facilities and information, can reliably estimate the required parameters. The use of modern metaheuristic algorithms to solve these multi-objective problems is one of these solutions. So far, multi-objective algorithms have been employed in solving problems such as Water Resources Allocation [8–11], Water Treatment Operations [12–15], Groundwater Management [16–19], Irrigation Purposes [20–23], Water Distribution Systems [24–27], Energy-Water Nexus [28–31], and Reservoir Operations [32–35].

Previous research has shown that the MOEPO algorithm has not been used in any of the studies related to water resources and agricultural optimization. In addition, none of the studies provided a comprehensive model as a proposed model for the multi-objective optimization of supply and demand in the agricultural section. Therefore, in this study, both supply and demand optimization were performed for the first time using MOEPO and crop model programming for the first time.

2. Materials and Methods

2.1. Study Area

In this study, Karaj Dam was considered a source of water supply, and the irrigation network covered agricultural lands as water consumers. Figure 1 shows the location of the study area and the farming lands. Among the 30,000 hectares covered by this network, only 23,000 hectares can be irrigated. Most crops, such as wheat, barley, fodder corn, alfalfa, tomato and cucumber, have been cultivated in this plain. The irrigation season typically begins in the first decade of March and continues through the end of the first decade of December. Table 1 summarizes the crop patterns and cultivated areas. In addition, information about the cultivation date of each crop based on field studies is presented in Table 2.

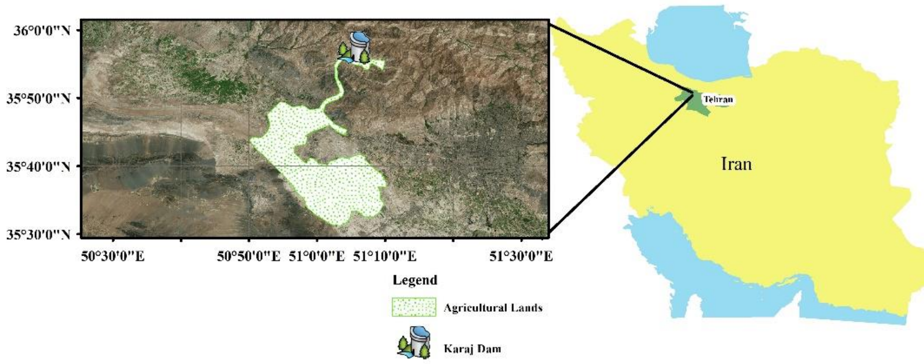


Figure 1. Karaj dam as a source of water supply and agricultural lands as water consumers.

Table 1. Under cultivation area of each crop in the Karaj plain irrigation network.

Crop/Fruit Crop	Wheat	Barley	Corn	Alfalfa	Cherry	Apple	Tomato	Cucumber
Under Cultivation Area (%)	27	14.7	30	2.8	10	12.7	1.4	1.4
Under Cultivation Area (ha)	6210	3381	6900	644	2300	2921	322	322

Table 2. Cultivation date of each crop.

	Alfalfa	Summer Cucumber	Spring Cucumber	Tomato	Corn	Barley	Wheat
Cultivation Date	**13th**	**13th**	**1st**	**7th**	**15th**	**21st**	**12th**
Month				**Growth Period**			
October	Init *	Init-Dev **					
November	Dev	Dev					
December	Dev	Dev					
January	Dev	Dev					
February	Dev	Dev					
March	Dev-Mid ***	Mid					
April	Mid	Late ****		Init	Init-Dev		Init-Dev
May	Late	Harvest	Init-Dev	Dev	Dev		Dev-Mid
June	Harvest		Dev-Mid	Dev-Mid	Dev-Mid	Init-Dev	Mid
July			Mid	Mid	Late	Dev	Late Season
August			Late	Late		Dev-Mid	Harvest
September			Harvest			Harvest	

* Initial; ** Crop Development; *** Mid-Season; **** Late Season.

To provide adaptation strategies and increase regional resilience, the first step is to identify and evaluate the effects of climate change on the basin and determine the input parameters. Data for temperature, precipitation and runoff were obtained from recent research [36]. The Penman–Monteith formula was used to calculate the ET0 (Reference Evapotranspiration). Four strategies were considered in managing agricultural water consumption (Changing Cultivation Dates (CCD), Deficit Irrigation (DI), Improving Irrigation Performance (IIP), and Optimizing the Crop Pattern (OCP)). To study the effect of these strategies on water consumption and crop yield in the baseline and future periods (under the influence of climate change), a combination of crop model programming and a multi-objective optimization algorithm (MOEPO) was employed.

Finally, to manage the optimal supply of water from the dam reservoir, minimize the Vulnerability, and maximize the Reliability Indexes, the MOEPO optimization algorithm was used, and the optimal allocation rules were obtained. Below are a few brief descriptions of the formulas and methods used in this study.

2.2. Models

The model related to the four AS was prepared as a single-objective non-linear program to maximize WUE (Equation (1)).

$$W_1 = \mathrm{Max}(\mathrm{WUE_i}) = \mathrm{Y_a}/\mathrm{IR_{i,j}} \tag{1}$$

where $\mathrm{Y_a}$ is crop yield in kilograms, $\mathrm{IR_{i,j}}$ indicates irrigation water allocated to crop in cubic meters.

The OCP optimization model was defined as a dual-objective model based on optimal allocation between different plants and crop profit maximization. The period of the balance equations was considered fixed for the whole model and was equal to the irrigation cycle of the region (10 days). The objective functions were maximizing the total gross income and minimizing the volume of water released from the dam reservoir (Equations (2) and (3)).

$$Z_1 = \mathrm{Max} \sum_{i=1}^{n} [P_i(Y_C)_i - C_i]A_i \tag{2}$$

$$Z_2 = \mathrm{Min}\left(\mathrm{IR_{i,j}}\right) \tag{3}$$

where

n: Number of crops,
i: Crop index,

Z_1: Total farmers' income (Rial),
P: Crop production price (Rial/Kg),
C: Crop production cost (Rial/ha),
A: Under cultivation area (ha),
Y_C: Relative yield (dimensionless), which was calculated using seasonal production.

The optimization of this part was done using the MOEPO algorithm. The amount of evapotranspiration was calculated by employing the methods provided in Appendix C. Utilizing the plant coefficient and related correction methods (provided in FAO 56 and 24), the ET0 was calculated for each product. Model performance is adapted to actual conditions by determining the constraints of each objective function. The constraints used in this study included water moisture in the soil, plant water requirement, irrigation water allocated to the plant, water allocation to the plant, actual evaporation and transpiration, water balance and the limitation of the cultivated area. For more information about this section, refer to Appendix A.

2.3. Supply Section

This study investigated increasing reservoir operation resilience by minimizing the Vulnerability (Equation (4)) and maximizing the Reliability Indexes (Equation (5)).

$$\text{Minimize } F(u_1) = \frac{\sum_{t=1}^{T}(D_t - Re_t | Re_t < D_t)}{\left[N_{t=1}^{t}(Re_t < D_t)\right] D_{max}} \ \forall t = 1, 2, \ldots, T \tag{4}$$

$$\text{Maximize } F(u_2) = \frac{N_{t=1}^{T}(D_t - Re_t | Re_t > D_t)}{T} \ \forall t = 1, 2, \ldots, T \tag{5}$$

In the above equations:

$F(u_1)$: Objective function related to the Vulnerability Index,
$F(u_2)$: Objective function related to the Reliability Index,
D_t: Demand volume in the t period,
D_{max}: Maximum demand in the t period,
Re_t: Released volume from the reservoir in the t period,

For more information on calculating the parameters and constraints intended for the objective functions, refer to Appendix B.

As defined in Equation (6), three operation rules (scenarios) were determined.

$$Re_{it} = g_{it}(Q_{it}, S_{it}, D_{it}) \ i = 1, 2, 3 \ and \ t = 1, 2, \ldots, T \tag{6}$$

where $g_1(Q_{1t}, S_{1t}, D_{1t})$ was the first operation rule calculated for the baseline conditions (first scenario), $g_2(Q_{2t}, S_{2t}, D_{2t})$ was applying the baseline rules to calculate water allocation for the future period, and $g_3(Q_{3t}, S_{3t}, D_{3t})$ was the third calculated rule, in which reservoir operation rules were calculated for the future period (2020–2040) based on future supply and demands (using future data).

2.4. MOEPO Algorithm

The MOEPO (Multi-Objective Emperor Penguin Optimizer) extends the capabilities of the existing Emperor Penguin Optimizer (EPO) to solve multi-objective problems. The algorithm introduces the concept of the dynamic archive, which has the property of caching non-dominated Pareto optimal solutions. More information about this algorithm and its application can be found in [37]'s research.

3. Results

The average water requirement for crops and agricultural demand will increase by 17% to 24% and 27%, respectively, in the future. Meanwhile, the total annual average water in the reservoir will decrease by 35% (see Appendix C for more information). These results indicate that if the area under cultivation remains constant or if the current cultivation and irrigation methods are continued in the future, the Karaj dam reservoir will not be able to supply the demands; therefore, in this study, supply and demand management strategies were employed. The results of these approaches are mentioned.

3.1. Demand Management

Since the irrigation period in this area is seven days, the intervals of CCD were considered 7, 14, 21 and 28 days. Based on Table 2, CCD in the baseline reduced WUE. Setting the cultivation date 7, 14, 14, 28, 28 days earlier led to an increase in WUE for tomato, wheat, corn, barley and cucumber, respectively, in the future period.

According to the Ministry of Agriculture-Jahad announcement, the average performance of Iran's irrigation network is about 30%, while the performance of Karaj's irrigation network is about 38%. The results related to the performance change illustrate that, based on the existing capital constraints and management policies, IIP, to about 48%, will reduce the water demand in study periods by almost more than 10%.

In this study, DI was considered uniform throughout the plant growth period. DI of 15% and 30% were considered to investigate the effect on WUE. According to Table 3, a DI of 15% improves WUE in wheat, barley, cucumber and alfalfa. However, the WUEs of corn and tomato have improved by applying 30%.

Table 3. WUE comparison for two strategies: CCD and DI in the baseline and future.

Crop	Time Step (Days)	WUE Ratio in the New Cultivation Date to the Primary Date				WUE Ratio in the DI to Full Irrigation		
		Bring Forward		Postpone				
		Baseline	Future	Baseline	Future	Percentage of DI	Baseline	Future
Wheat	7	0.87	1.14	0.72	1.08	**0.15**	**1.2**	**1.4**
	14	0.85	**1.37**	0.68	1.04			
	21	0.91	1.12	0.66	1.01	0.3	1.14	1.26
	28	0.83	1.26	0.58	0.78			
Barley	7	0.91	1.03	0.9	0.85	**0.15**	**1.23**	**1.4**
	14	0.84	1.15	0.82	0.66			
	21	0.82	1.12	0.91	1.03	0.3	1.16	1.28
	28	0.73	**1.18**	0.89	0.72			
Corn	7	0.85	1.12	0.72	1.05	0.15	1.17	1.35
	14	0.92	1.16	0.59	1.03			
	21	0.76	1.09	0.44	0.9	**0.3**	**1.25**	**1.43**
	28	0.68	1.14	0.43	0.85			
Tomato	7	0.85	**1.23**	0.73	0.86	0.15	1.19	1.27
	14	0.81	1.11	0.72	0.77			
	21	0.71	1.13	0.74	0.98	**0.3**	**1.2**	**1.32**
	28	0.56	1.14	0.61	0.78			
Cucumber	7	0.73	1.1	0.74	0.86	**0.15**	**1.22**	**1.38**
	14	0.63	1.14	0.73	0.77			
	21	0.43	1.13	0.72	0.98	0.3	1.15	1.36
	28	0.41	**1.23**	0.61	0.78			
Alfalfa	Alfalfa is a perennial herbaceous crop, so CCD is not considered for this crop.					**0.15**	**1.11**	**1.18**
						0.3	1.09	1.11

According to Table 4, in the future period, all crops yield will be reduced. In contrast, irrigation water demands for these crops will increase by about 220 to 580 MCM per hectare. Therefore, following the current cultivation pattern is not only economically affordable but also puts intense pressure on the region's water resources. In this regard, to improve the region's resilience to climate change, the optimized crop pattern model results were used. Based on this model, following the new optimal cultivation pattern and reducing the area under cultivation by 30% in the basic and future periods will increase the total profit of the farmers by 24% and 5%, respectively, and the volume of consumed water will reduce by 9% and 11%, respectively.

Table 4. Comparison of profit and released water for current and optimized crop patterns in the baseline and future period.

		Crop		Wheat	Barley	Corn	Alfalfa	Tomato	Cucumber	Sum
Baseline	Current Situation	**Crop Production cost**	(Rial)	30,214.3	14,384.6	18,233	17,562	15,560.8	20,509.7	116,464
		Sales Price	(Rial)	75,000	34,000	35,250	58,000	36,780	39,652	278,682
		Average Annual Crop Yield	(Kg/ha)	3737.8	3689	35,065	10,099	34,042.4	45,071.6	131,484
		Irrigation Water Per Hectare	(MCM)	995.8	825.3	1354.7	1885.1	1336.1	2066.7	8463.7
		Cultivated Land	(ha)	6210	3381	6900	644	322	322	17,779
		Initial profit	(Rial)	1.74×10^{12}	4.24×10^{11}	9×10^{12}	4×10^{11}	4×10^{11}	5.7×10^{11}	1.2×10^{13}
		Total Released Water	(MCM)	6,183,838	2,790,188	9×10^{6}	1×10^{6}	430,215	665,486	2.1×10^{7}
	Optimized Pattern	**Cultivated land**	(ha)	14.9	4.1	924.7	1918.6	7625.4	1791.3	12,279
		Initial profit	(Rial)	4.18×10^{9}	5.17×10^{8}	1×10^{12}	1×10^{12}	9.5×10^{12}	3.2×10^{12}	1.5×10^{13}
		Total Water released	(MCM)	14,832	3401.4	1×10^{6}	4×10^{6}	1×10^{7}	3,702,191	1.9×10^{7}
Future	Current Situation	**Crop Production cost**	(Rial)	30,214.3	14,384.6	18,233	17,562	15,560.8	20,509.7	116,464
		Sales Price	(Rial)	75,000	34,000	352,50	58,000	36,780	39,652	278,682
		Average Annual Crop Yield	(Kg/ha)	3678.3	3676.3	34,624	9997.3	33,923.5	44,968.9	131,090
		Irrigation Water Per Hectare	(MCM)	1257.7	1054.1	1774.1	2507.5	1685.4	2648.6	10,927.4
		Cultivated Land	(ha)	6210	3381	322	644	322	6900	17,779
		Initial profit	(Rial)	1.71×10^{12}	4.23×10^{11}	4×10^{11}	4×10^{11}	4×10^{11}	1.1×10^{13}	1.4×10^{13}
		Total Released Water	(MCM)	7,810,602	3,564,025	852,848	2×10^{6}	542,701	1.2×10^{7}	2.7×10^{7}
	Optimized Pattern	**Cultivated land**	(ha)	51.2	41.9	942.7	1937	7661	1874	12,507.8
		Initial profit	(Rial)	1.41×10^{10}	5.23×10^{9}	1×10^{12}	1×10^{12}	9.6×10^{12}	3×10^{12}	1.5×10^{13}
		Total Water released	(MCM)	64,434.8	44,145.2	2×10^{6}	5×10^{6}	1.3×10^{7}	3,324,551	2.4×10^{7}

The amount of water demand was calculated based on the selected CCD, DI, IIP and OCP in the long-term baseline and future series and entered into the MOEPO as an independent variable along with other independent variables; the optimal operation rules of the reservoir were extracted. The results of this section are presented as follows.

3.2. Demand Management

A multi-objective water allocation model was employed to manage the supply from the reservoir by applying four AS to minimize the Vulnerability and maximize the Reliability Indexes. Figure 2 illustrates the results of the Pareto curves for future and baseline periods, considering the application and non-application of AS in the agricultural section.

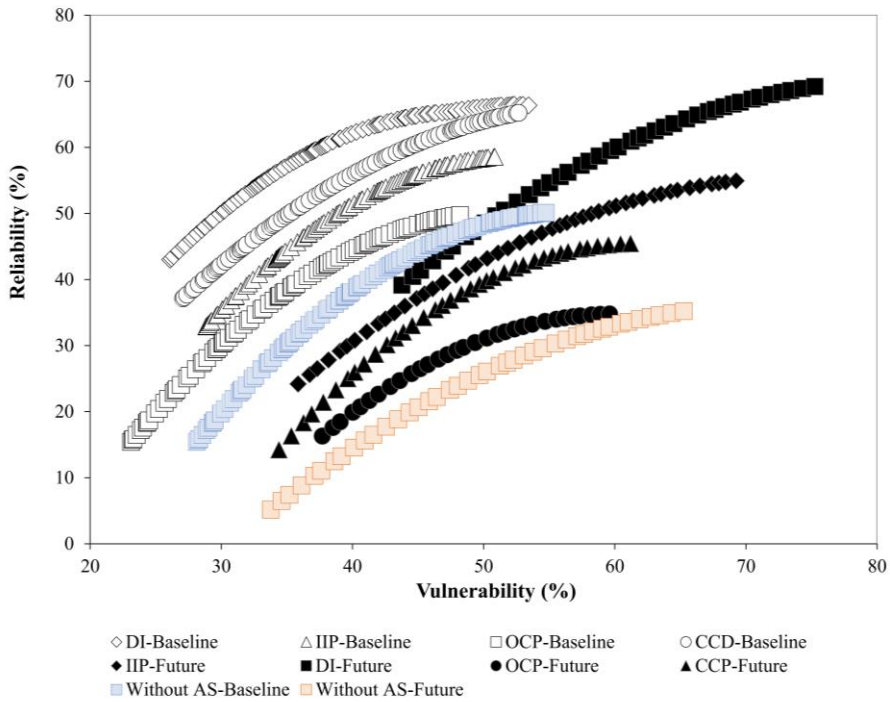
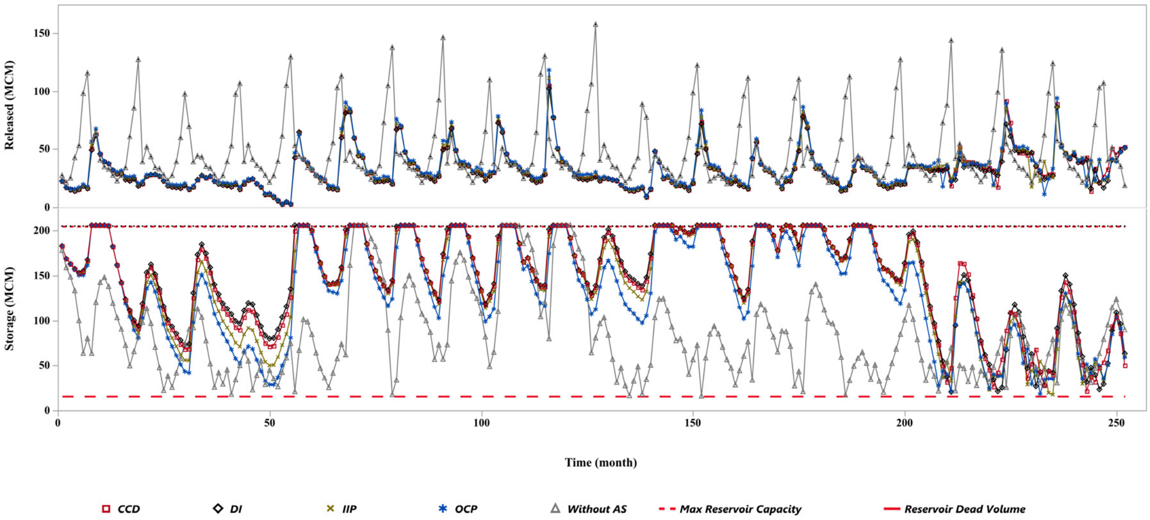


Figure 2. Comparison of Pareto curves in the baseline and future periods.

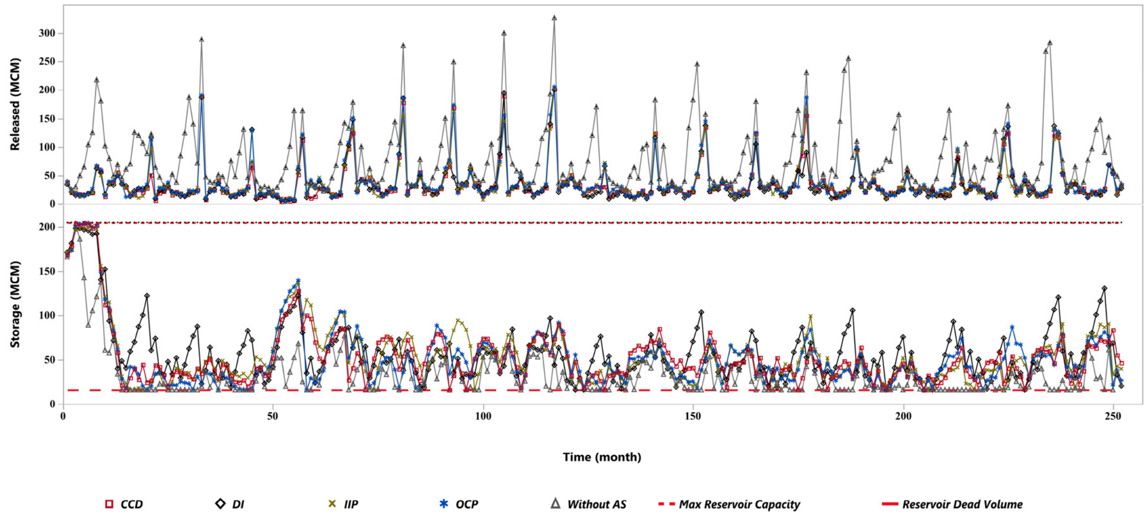
Consideration of AS decreased the Vulnerability Index and increased the Reliability Index, as shown in Figure 2. In the next step, the optimal rules for the baseline and future conditions for water demand were evaluated. A comparison was made in this section between the optimal rules obtained from the baseline conditions (scenario 1), applying optimal baseline rules for the climate change conditions (scenario 2), and applying optimal rules for the climate change conditions (scenario 3). In Figure 3, the first and third scenarios' results of 45% vulnerability, considering or without considering four AS, are provided, respectively.

As shown in Figure 3a, in 171 months of the baseline period, reservoir storage in the non-AS state ranged from 28 to 112 MCM. In contrast, using AS, the storage volume reservoir ranged between 116 and 205 (max reservoir capacity) MCM in 188 months (on average). As a result, about 80% less water was released from the reservoir than if AS was not used. This indicated the reservoir's ability in the baseline period (1985–2005) to meet the demands and showed the superiority of the multi-objective optimization solution over the current management solution in allocating water from the dam reservoir.

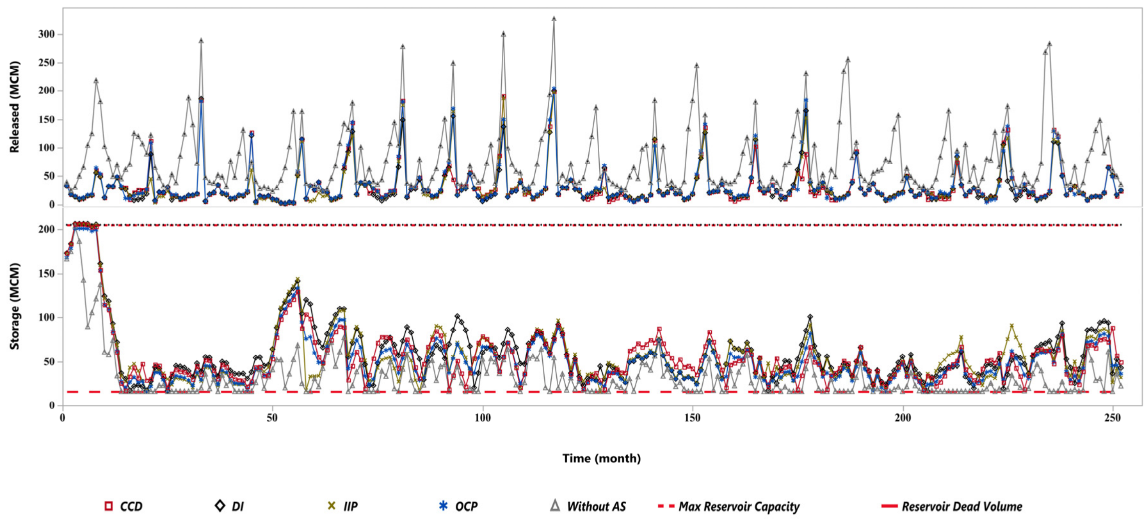
As shown in Figure 3b,c, without AS for 161 months, reservoir storage was between 16 (dead volume) and 30 MCM. Under the second scenario, in 200 months, the storage volume in all four AS was between 20 and 80 MCM, and under the third scenario, in 230 months, it was between 20 and 100 MCM. The storage volume reached more than 200 MCM in just six months for both scenarios. The maximum released volumes for the OCP were 204 and 206 million cubic meters, respectively, for the second and third scenarios. Based on the figures, it can be stated that the total average released volume in scenario three was reduced by 14, 15, 11 and 13%, respectively, compared to scenario two, corresponding to CCP, IIP, DI and CCD. Accordingly, the allocation rules derived from the third scenario were superior to those of the second scenario. In addition, employing AS reduced the released volume and increased reservoir capacity in all scenarios.



(**a**)



(**b**)



(**c**)

Figure 3. Investigation of released and storage volume: (**a**) first scenario; (**b**) second scenario; (**c**) second scenario.

Table 5 compares the results of the Pareto point corresponding Vulnerability Index of 45% in the three scenarios with/without four adaptation solutions. Comparing the objective functions in the first and second scenarios shows that the rules derived from the baseline are not appropriate for future conditions. In comparing the second and third scenarios, it was found that the first and second objective functions would be improved if future rules (dam operation in climate change periods) were applied in the third scenario.

Table 5. Comparison of the three scenarios: Reliability Index corresponding to a Vulnerability Index of 45%.

Scenario	State	Reliability Index (%)	Changes to No AS State (%)
First	OCP	56	16.67
	IIP	69	43.75
	DI	74	54.16
	CCD	71	47.91
	Without AS	48	—
Second	OCP	25	31.57
	IIP	27	42.10
	DI	38	100
	CCD	27	42.10
	Without AS	19	—
Third	OCP	41	41.37
	IIP	48	65.51
	DI	53	82.75
	CCD	45	55.17
	Without AS	29	—

According to Table 5, the DI is the most appropriate among all AS. In baseline conditions, considering the Vulnerability Index of 45%, the Reliability Index of DI, IIP, CCD and OCP increased by about 54, 44, 48 and 17%, respectively, compared to without AS.

4. Discussion

Climate change in this study area reduced crop yield and increased the consumed water volume. These results are consistent with [38–40]'s studies.

Using AS (optimize the cultivation pattern, change the cultivation date and reduce irrigation) helps to reduce the amount of water consumed and increase WUE in the agricultural section. These results are consistent with those of [39,41]'s studies.

Using a management strategy in the supply section (multi-objective optimization of dam reservoir operation) improves two Indexes of Vulnerability and Reliability in the baseline and future. These results were confirmed in [42,43]'s studies.

5. Conclusions

Investigation of crops' water demand and supply indicated that in the period (2020–2040), all crops would face an increase in water demand, and the system will likely face stress in meeting the needs. In this regard, a series of demand and allocation management strategies were applied, and the results showed the following:

- During the baseline period, the WUE declined when the cultivation date was changed for all crops. However, it increased after the cultivation date was brought forward to 7, 14, 14, 28, 28 days for tomato, wheat, corn, barley and cucumber, respectively, in the future period.
- The DI application showed that wheat, barley, cucumber and alfalfa have a more pleasing WUE of a 15% DI, while corn and tomatoes have a higher WUE of a 30%.
- IIP to about 48% also reduced water demand by 10% in both study periods.
- The results related to crop pattern optimization and area under cultivation also showed that following the new optimal cultivation pattern and reducing the under-cultivation area by 30% in the base and future periods increased the total profits of farmers by

24 and 5 percent. Additionally, this optimized state reduced the volume of water consumption by 9 and 11 percent, respectively.

- Optimizing dam allocation showed that DI, IIP, CCD and OCP improved the Vulnerability and Reliability Indexes.
- The results of the scenario comparison indicated that the third scenario performed better than the first one. In addition, the objective function values in the first and second scenarios suggested that the baseline rules were not suitable for use in the future.
- Out of the four AS, the DI was the most appropriate.

As a continuation of this research, the combined effect of AS can be examined on the water consumption efficiency index. Other factors, such as changes in fertilizer consumption amount and type, can also be investigated as influencing product performance. To make this study more practical, farmers' levels of readiness and interest in implementing and applying each of these strategies can be evaluated with a questionnaire as part of a statistical study.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A.

Appendix A.1. Crop Model

The sensitivity and evapotranspiration coefficients were taken into account in the calculation of the crop irrigation function based on seasonal production. The relationship between Y_C (relative yield) and relative evapotranspiration is presented in Equation (A1) [44].

$$Y_C = \frac{Y_a}{Y_p} = \prod_{i=1}^{n} \left(\frac{ET_a}{ET_{max}} \right)^{\lambda i} \tag{A1}$$

In the above equation, parameters are defined as below:

Y_a: Actual yield (kg/ha),
Y_p: Maximum yield under management conditions that can be received with unlimited water supply potential (kg/ha),
ET_a: Actual evapotranspiration (mm),
ET_{max}: Maximum evapotranspiration (mm),
λi: Sensitivity index to water stress (Equation (A2)).

The problem with such models is the existence of sensitivity coefficients at different stages of growth. To resolve this problem, K_y coefficients for different stages of growth of many plants are reported in the 33rd Journal of Food and Agriculture Organization (FAO).

$$\lambda = 0.2418K^3 - 0.1768K^2 + 0.9464K - 0.0177 \tag{A2}$$

where K is yield reaction coefficient to water stress in different growth stages and is presented in the FAO-56 magazine.

Appendix A.2. Constraints

The following constraints were used in the crop model:

- Soil moisture: At the beginning of the irrigation season, it was assumed to be at the field capacity for all soils and crops. The soil water balance equation was employed to calculate soil moisture at other time intervals.
- Water requirement: Maximum water requirement of the crop was calculated based on the soil moisture depletion factor (which can be extracted from FAO 24), effective rainfall, maximum evapotranspiration, soil moisture and amount of total available soil water accessible to the plant.
- Reservoir release: Releasing water from the reservoir to meet irrigation requirements should always be less than the maximum release from the reservoir.
- Reservoir storage: The amount of water stored in a reservoir should be between the maximum and minimum storage volumes (dead volume), which is determined by the continuity of the storage volume.
- Actual evapotranspiration: Actual evapotranspiration is always less than or equal to maximum evapotranspiration. In this study, the maximum evapotranspiration was determined based on [45]'s method.
- Cultivated area: Each crop should have a specific range of cultivated areas (must remain within a certain limit).

For more information about the model and constraints, please refer to [41].

Appendix B.

Appendix B.1. Simulation and Optimization of Dam Operation

To simulate the behavior of the dam reservoir, the continuity equation (Equation (A3)) was used. In this equation, the time steps were considered monthly.

$$S_{t+1} = S_t + Q_t - LE_t - SP_t - R_{et} \tag{A3}$$

where S_{t+1} and S_t are reservoir storage volumes at the beginning and end of t and t + 1 periods, respectively, Q_t is amount of inflow volume to reservoir during the t period, R_{et} is the volume of release from the reservoir during the t period, SP_t is the amount of overflow volume from the reservoir at the beginning of the t period (Equation (A4)) and LE_t is the volume of losses due to evaporation from reservoir surface during the t period.

$$SP_t = \begin{cases} S_{t+1} - S_{max} & S_{t+1} \geq S_{max} \\ 0 & S_{t+1} < S_{max} \end{cases} \tag{A4}$$

where S_{max} is the maximum volume of reservoir capacity and S_{t+1} is reservoir storage volume at the beginning and end of the t + 1 period.

To achieve this maximum resilience, two objective functions were introduced in Equations (4) and (5).

Appendix B.2. Constraints

The constraints applied to reservoir operation are presented in Equations (A5) and (A6).

$$S_t \geq S_{min} \ \forall t = 1, 2, \ldots, T \tag{A5}$$

$$Re_t \geq 0 \ \forall t = 1, 2, \ldots, T \tag{A6}$$

where S_{min} is the minimum volume or dead volume of the reservoir.

In this study, penalty values were added to the objective functions if the constraints are violated, as shown in Equations (A7) and (A8).

$$\mathrm{Penalty1} = \mathrm{A}'\left\{\left(\frac{\mathrm{S_{min}} - \mathrm{S_t}}{\mathrm{S_{max}} - \mathrm{S_{min}}}\right)^2 + \mathrm{B}'\right\} \forall \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{A7}$$

$$\mathrm{Penalty2} = \mathrm{C}' \cdot \left(\frac{\mathrm{Re_t}}{\mathrm{D_{max}}}\right) + \mathrm{D}' \,\forall \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{A8}$$

where Penalty1 is the penalty function due to the violation of the constraint of Equation (A5) and Penalty2 is the penalty function is the specialized problem due to the violation of the constraint of the Equation (A6) and the coefficients A' to D' are the positive constants of the penalty function. In these cases, the penalty functions were added to the objective functions as follows (Equations (A9) and (A10)).

$$\mathrm{F}(\mathrm{u_1}) = \mathrm{F}(\mathrm{u_1}) + \mathrm{Penalty1}(\text{and Penalty2}) \,\forall \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{A9}$$

$$\mathrm{F}(\mathrm{u_2}) = \mathrm{F}(\mathrm{u_2}) + \mathrm{Penalty1}(\text{and Penalty2}) \,\forall \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{A10}$$

Appendix C.

Estimation of Irrigation Demand in the Future Period

To calculate ET_{0t}, it is impossible to have access to all of the necessary data, such as relative humidity and wind speed, in the future. For destemming ET_{0t}, FAO Penman-Monteith method was employed. This was done by selecting the relationship between temperature and relative humidity for the baseline period. The highest correlation between the temperature and the ET0 was obtained using the quadratic polynomial function relation (Figure A1).

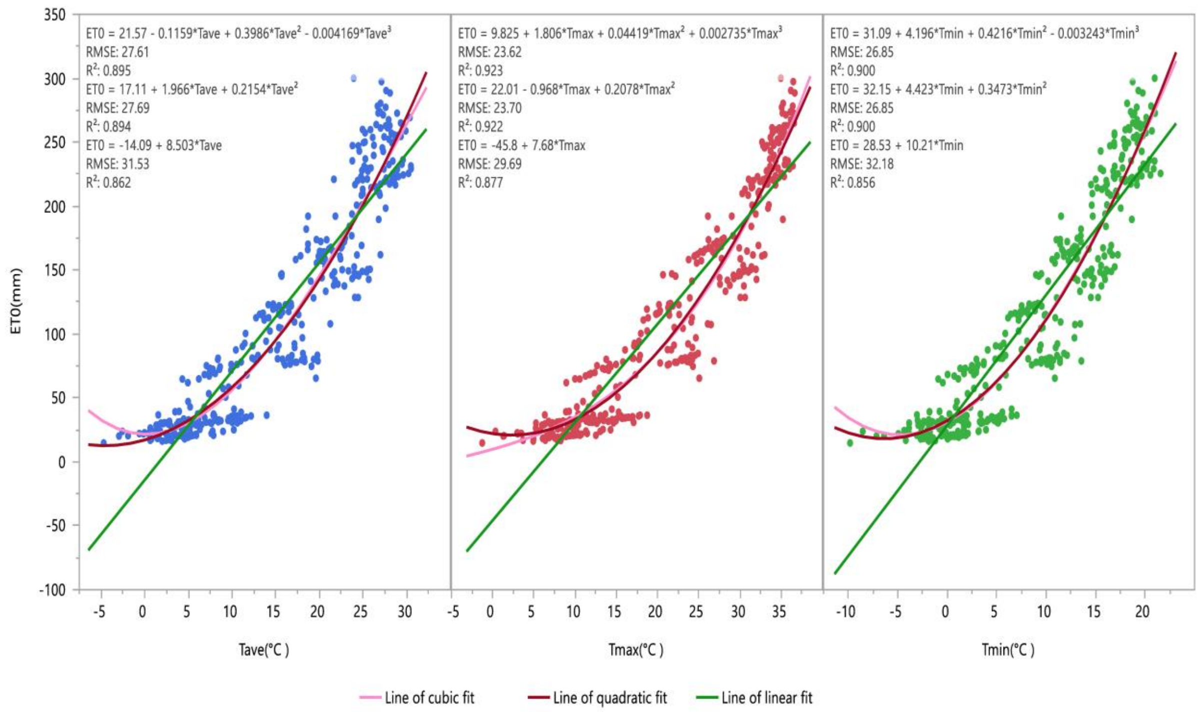

Figure A1. Relationship between mean, minimum and maximum temperature and ET0 estimated by the FAO Penman−Monteith method.

To obtain the amount of relative humidity in the future period, an exponential regression relationship was followed (Figure A2). It was assumed that the wind speed would remain similar to its baseline value in the future.

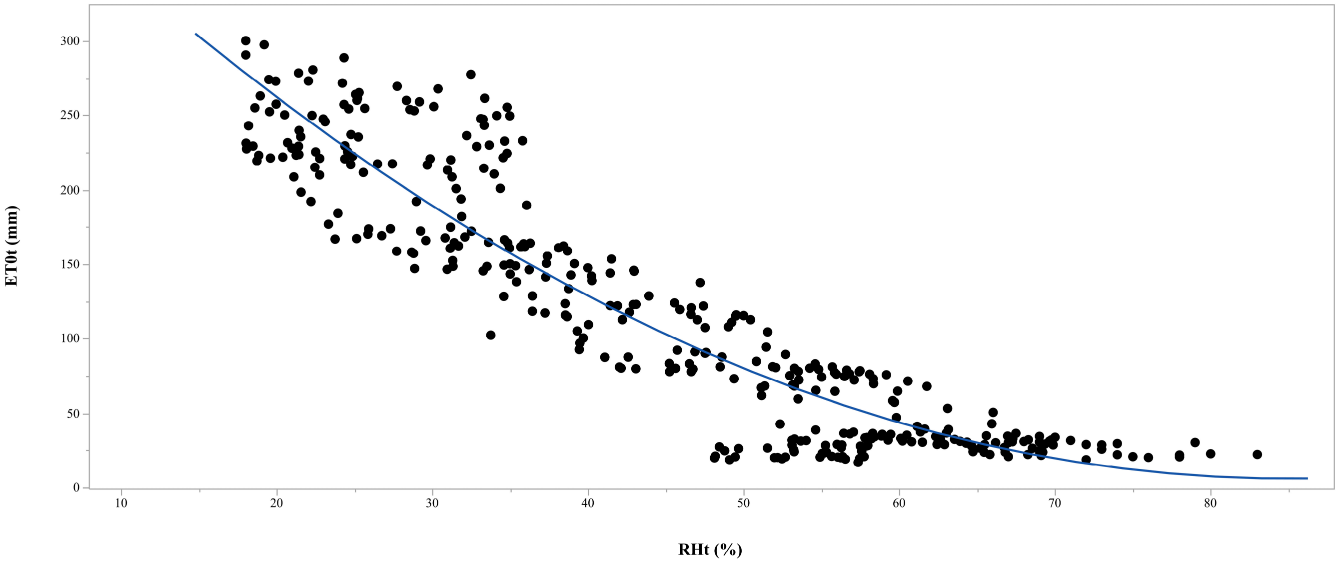

Figure A2. Correlation of ET_{0t} and RH_t in the baseline period.

The amount of future ET0 was calculated using these assumptions, and the crops' evapotranspiration (ET_c) was obtained by multiplying the crop coefficient with the estimated values. Table A1 shows the ET_c for past and future periods.

Table A1. Crops' annual ET_c from 1985 to 2005 and 2020 to 2040.

Crop	ET_c Baseline Period (mm)	ET_c Future Period (mm)	Future to Past Ratio	Percentage Change (%)
Wheat	504.85	594.36	1.18	17.73
Corn	634.32	796.97	1.26	25.64
Barley	440.12	517.55	1.18	17.59
Alfalfa	990.83	1193.44	1.20	20.45
Cucumber	916.86	1104.97	1.21	20.52
Tomato	551.35	664.04	1.20	20.44

The Effective precipitation (P_{eff}) was calculated by the SCS method, and finally, the annual irrigation demands were obtained (Tables A2 and A3).

Table A2. Average net annual irrigation demands from 1985 to 2005 and 2020 to 2040.

Crop	Baseline Demand (mm)	Future Demand (mm)	Future to Past Ratio	Percentage Change (%)
Wheat	380.97	477.94	1.25	25.45
Corn	530.29	674.14	1.27	27.13
Barley	315.82	400.57	1.27	26.83
Alfalfa	732.08	952.84	1.30	30.16
Cucumber	783.16	1006.47	1.29	28.51
Tomato	513.01	640.45	1.25	24.84

Table A3. Average total volume of irrigation demands from 1985 to 2005 and 2020 to 2040.

Crop	Future Volume (MCM)	Baseline Volume (MCM)	Future to Past Ratio	Percentage Change (%)
Wheat	78.11	62.26	1.25	25.46
Corn	122.41	96.29	1.27	27.13
Barley	35.64	28.10	1.27	26.83
Alfalfa	16.15	12.41	1.30	30.14
Cucumber	8.53	6.64	1.28	28.46
Tomato	5.43	4.35	1.25	24.83

As shown in the above table, the volume of water demand will for the future period for all crops. The demand for some crops, such as alfalfa and cucumber, will increase by 30.14 and 28.46 percent, respectively, compared to the baseline period. For further investigation, the results of comparing the long-term average monthly demand volume in the baseline and the future with the inflow into the reservoir are presented in Figure A3. In comparison to the baseline period, the amount of water released from the reservoir to meet demands will increase in the future. Thus, the total average annual volume of released water to meet agricultural demands (entire crops and fruit crops) in the baseline and future is 234.82 and 297.55 million cubic meters, respectively. This indicates that the released volume to meet the demands will increase by about 27%.

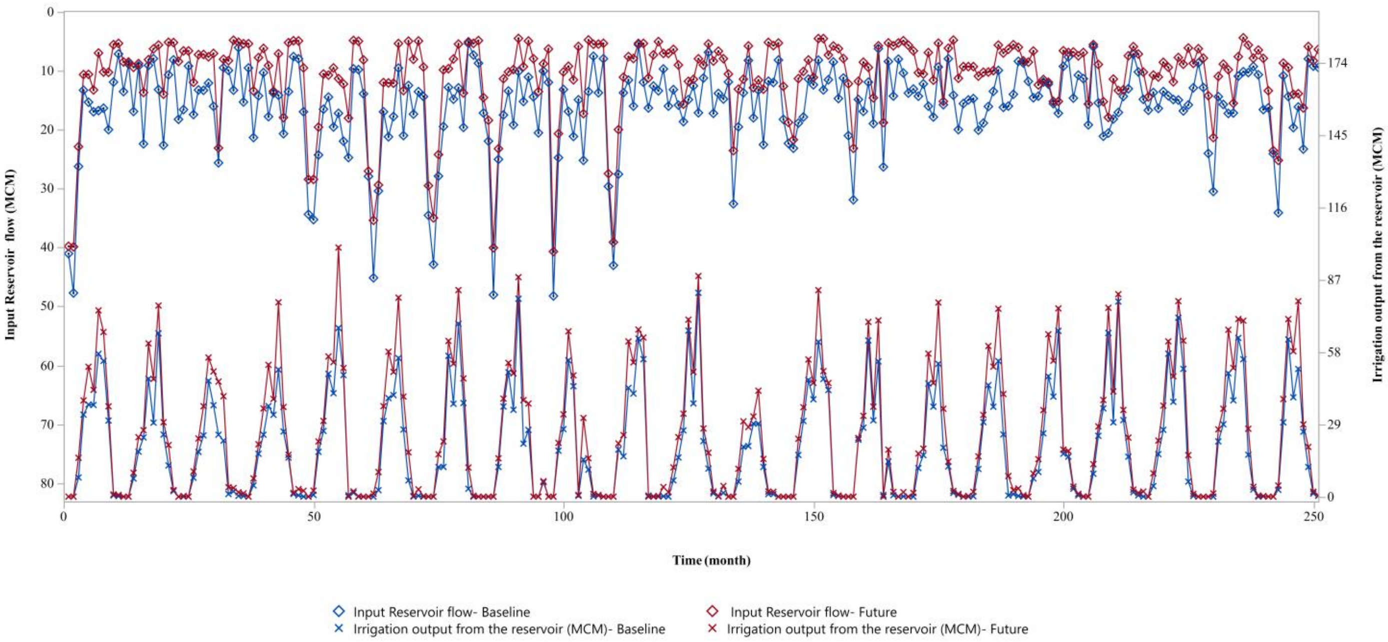

Figure A3. Comparison of water demand volume in the baseline and future intervals with inflow to the reservoir.

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