



# Optimal land allocation and irrigation scheduling to maximize the economic utility

Parisa Kahkhamoghaddam<sup>1</sup> · Ali Naghi Ziaei<sup>1</sup> · Kamran Davary<sup>1</sup> · Amin Kanooni<sup>2</sup> · Sedigheh Sadeghi<sup>3</sup>

Received: 11 September 2023 / Accepted: 7 February 2024 / Published online: 17 March 2024  
© Springer Nature Switzerland AG 2024

## Abstract

Attaining sustainable agriculture requires water consumption management. A water allocation optimization model was developed for the Moghan irrigation network (northwest of Iran) based on the AquaCrop plug-in model. The genetic algorithm was applied to optimize water allocation for five main crops, including wheat, first-cultivation maize, second-cultivation maize, soybeans, and alfalfa. The heuristic economic utility (*EU*) function was used as the objective function to optimize water allocation. In this function, drained water salinity was applied as a penalty factor to the total benefit, and soil salinity deterioration due to irrigation was also considered as a factor in each crop's benefit. The results showed that the optimal allocated water depth was 17% less than the normal water consumption. Moreover, the application of soil water salinity coefficients did not affect the ratio of *EU* to *EB* (economic benefits) for wheat and alfalfa. However, first-cultivation maize, second-cultivation maize, and soybeans cultivation led to a reduction in *EU* within the study area. A combination of the crops cultivation led to a change in river water quality and an 8.2% reduction in the ratio of *EU* to *EB* function.

**Keywords** Salinity · AquaCrop model · Optimization · Moghan irrigation network · Irrigation scheduling

## Introduction

Since agriculture is the largest consumer of water among different sectors, optimal water usage in agriculture has the most significant effect on water management. To overcome the water shortage and make maximum use of the limited available water, the allocation and scheduling of irrigation water should be done optimally (Kanooni & Monem, 2014). The optimal allocation and irrigation scheduling have been conducted based on two approaches: fixed demand (Monem and Namdariyan., 2005; Mathur et al., 2009) and variable demand (Kanooni & Monem, 2014; Oad et al., 2009). In the

first approach, irrigation is scheduled with the assumption of constant demand and without knowing the water needs of the irrigation unit and based on the consumers' request. However, in the second approach, crop type, climatic conditions, and soil moisture are influential, and optimal irrigation scheduling is determined based on actual demands (Li et al., 2020).

The simulation models used in irrigation programs provide the possibility of checking and predicting the system's behavior in the face of various variables, saving costs and making more appropriate decisions. They also reduce the limitations of field research, including time-consuming and lack of human resources (Bastiaanssen et al., 2007). The AquaCrop model has been evaluated for irrigation scheduling in different climatic conditions (Guo et al., 2021; Li et al., 2018; Linker et al., 2016). In recent years, irrigation scheduling has been optimized using plant simulation models such as AquaCrop instead of extracting experimental production functions (Kheir et al., 2021; Martinez-Romero et al., 2021). Meta-heuristic algorithms, such as genetic algorithm, has been used for various optimizations, including irrigation scheduling. The Genetic algorithm has led to reasonable outcomes in different fields (Rath et al., 2018; Wabela et al., 2022; Yao et al., 2019). The single-objective

✉ Ali Naghi Ziaei  
an-ziaei@um.ac.ir

<sup>1</sup> Water Science and Engineering Department, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran

<sup>2</sup> Water Science and Engineering Department, Faculty of Agriculture and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran

<sup>3</sup> Faculty of Mathematical Sciences, Department of Applied Mathematics, Ferdowsi University of Mashhad, Mashhad, Iran

optimization for irrigation scheduling has been gradually replaced by multi-objective procedures, which have conflicting objectives without a unique optimal solution (Guo et al., 2021). The AquaCrop model was used to optimize the winter wheat irrigation schedule under dry, normal, and wet hydrological scenarios. The optimization objectives in their research included crop yield, irrigation water use efficiency (WUE), and economic benefit (*EB*). The results showed that the optimal irrigation scheduling performed better than the usual farmers' schedule. It also led to an increase in crop yield, *EB*, and WUE (Guo et al., 2021). This study was conducted only for one crop in various hydrological scenarios. García-Vilaa and Fereres (2012) used AquaCrop and a farm-scale optimization model to optimize the water consumption of some selected crops. They showed that using crops with lower water consumption freed up water to produce crops with more water consumption and higher economic value. They used the AquaCrop model to extract the production functions of the crops, and the AquaCrop model was not combined with the optimization model for successive executions. The crop yield, *EB*, and water charge were among determining factors for irrigation scheduling and water resource allocation that should be considered during optimization (Rath et al., 2018; Wang et al., 2008).

Past research shows that the drained water salinity of rivers (Somlyody, 1998; McBride, 2002), and soil salinity (Connor et al., 2012; Nemoto & Sasakuma, 2002) are factors that affect crop yield and optimal water resources allocation.

The increase in the environmental pollutants loaded into rivers through industrial, urban, and agricultural activities has resulted in changing the rivers' water quality indices (Jahin et al., 2020). Salinity is one of the primary indices of rivers' water quality, which quantifies water-soluble salts (Quinn, 2011). Enhancing water quality and reducing its salinity requires efficacious efforts to manage water resource utilization (Somlyody, 1998; McBride, 2002). To this end, managing farms drained water entering the rivers is one of the most effective practices to preserve long-term cropping yield benefits.

Water and soil salinity are environmental hazards leading to soil deterioration and a reduction in agricultural efficiency, especially in arid and semi-arid regions such as Iran (Connor et al., 2012; Alizade Govarchin Ghale et al., 2017). Furthermore, salinity is a major factor in limiting crop growth by reducing root water and nutrient uptake (Wilkinson, 2000). The increase in soil electrical conductivity brings about salt stress and crop biochemical and physiological changes, which reduces crop growth and yield (Nemoto & Sasakuma, 2002). Hence, soil physical and chemical properties, irrigation water quality, and their management play an important role in long-term farm management (Douaik, 2006).

The *EB* function is considered the main objective function in most studies related to irrigation scheduling (Rath

et al., 2018; Kumar & Yadav., 2019), while the economic utility function (*EU*), which in addition to *EB*, considers the long-term environmental effects and the production sustainability, has not been evaluated. In this study, the heuristic *EU* function is used instead of the *EB* for optimal irrigation water allocation. This heuristic function is proposed instead of the *EB* function by applying two coefficients of soil salinity and the salinity of drained water to the river. By applying the two coefficients, in addition to maximizing the *EB* in the same year, the long-term environmental effects caused by the cultivation of different crops, soil quality preservation, river water quality variation, sustainable agriculture, and long-term benefits are also evaluated. To evaluate crop yield response to water, the AquaCrop plug-in model has been used instead of experimental production functions such as Doorenbos and Kassam (Doorenbos et al., 1979). Therefore, the present study aims to maximize the *EU* and optimal water and land allocation for five main crops in a part of the Moghan irrigation network in the northwest of Iran using the genetic algorithm optimization method incorporated with the AquaCrop model.

## Materials and Methods

### Study Area

The Moghan Plain is located in the northwest of Iran. The Moghan irrigation network is fed by the Aras River and irrigates 72,000 ha of the Moghan Plain agricultural lands, as shown in Fig. 1. According to the statistics and information of the regional water company of Ardabil, a part of Aras River water extracted by the Moghan network, the other part enters the Mil network of Azerbaijan, and the rest overflows the diversion dam and flows back to the Aras River and finally leads to the Caspian Sea. The volume of and salinity of water transferred back to the Aras River, for the years 2011–2020 are shown in Fig. 2 and Fig. 3. The study site is part of this network, located in the Pars-Abad region and irrigated by canal M with a covered area of about 2000 ha and 3 m<sup>3</sup>/s capacity. This area was considered an irrigation analysis unit (IAU). In the 2020 agricultural year (Sep. 2020–Aug. 2021), the main cultivated crops in the study area were wheat, grain maize (first cultivation maize, second cultivation maize), soybeans, and alfalfa. In this research, mean long-term data (20 years) of the Pars-Abad weather station were used to prepare meteorological information (Fig. 4). Table 1 shows some information related to the studied crops. The information about the crops in the region was obtained from the Agricultural Organization of Ardabil Province. The unit price of the crops was also collected from the reports of the Iranian Statistics Center. According to the Agricultural

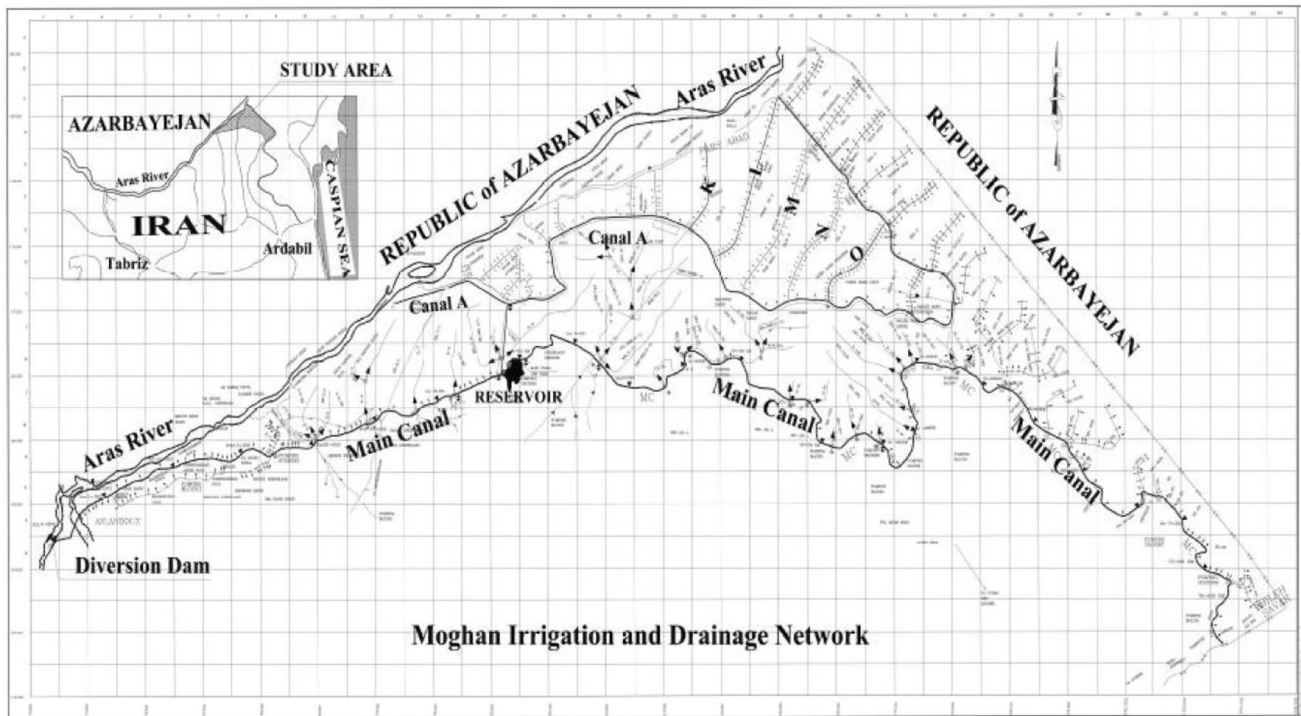


Fig. 1 Location of Moghan irrigation network

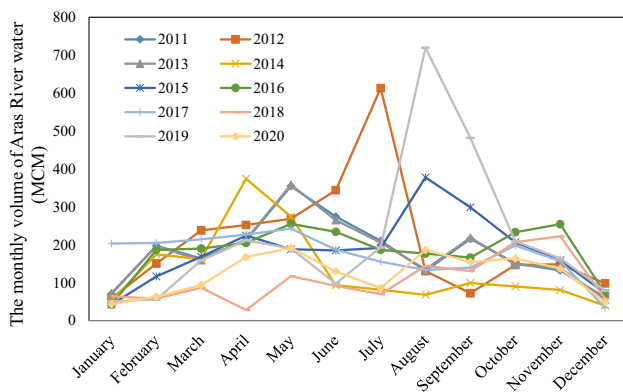


Fig. 2 The monthly volume of Aras River water after the diversion dam for the years 2011–2020

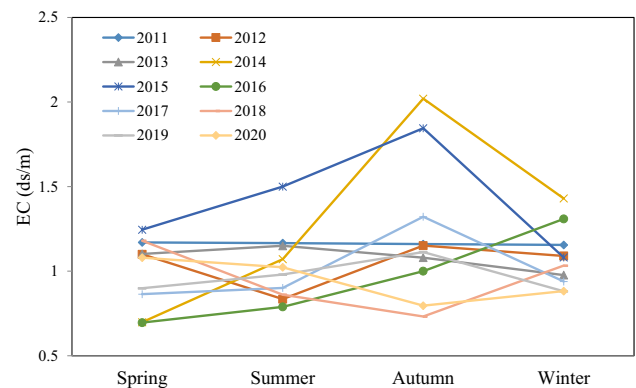


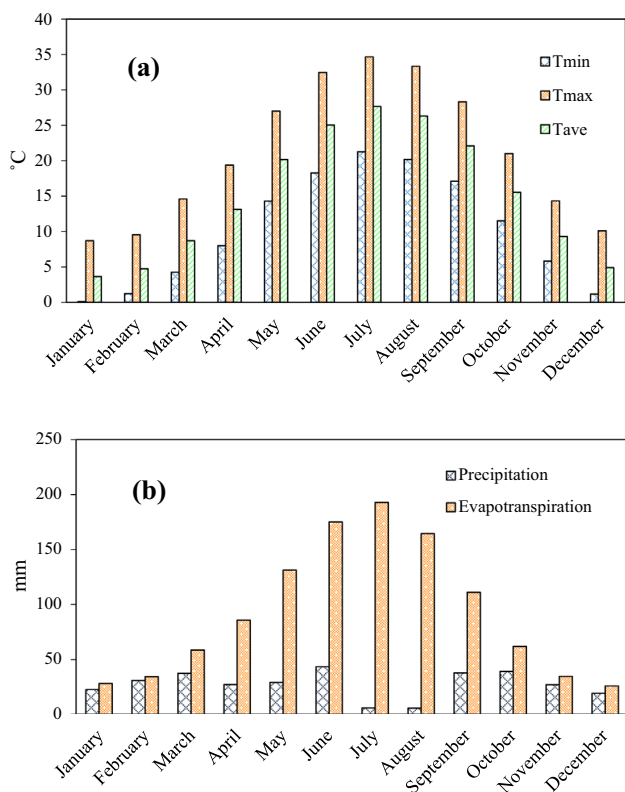
Fig. 3 Aras River seasonal water salinity after diversion dam for the years 2011–2020

Water Price Stabilization Law, average water charge from modern networks is 3% of the crop yield.

### AquaCrop Model

The AquaCrop model is an advanced program published by the World Food and Agriculture Organization (FAO). The development of this model is based on biophysical interactions in the plant-soil-atmosphere system (Sandhu & Irmak, 2019). Evapotranspiration calculation in this program is based on the dual crop coefficient method (Steduto et al., 2012). This model

simulates the crop yield as a function of water consumption in different irrigation regimes. It also connects crop yield to crop water consumption and estimates the amount of biomass resulting from actual crop transpiration through normalized water productivity, which is the core of AquaCrop’s growth engine (Steduto et al., 2012). In the AquaCrop model, the yield is calculated based on the product of crop dry matter ( $B$ ) and the harvest index ( $HI$ ) (Eq. 1). Separation of yield ( $Y$ ) into the dry matter and harvest index distinguishes the relationship between environment and dry matter production with the relationship between environment and harvest index. Therefore,



**Fig. 4** Average long-term minimum, maximum, and mean daily temperature values (a) and average long-term values of monthly rainfall and evapotranspiration (b) in the Pars-Abad weather station

the effect of water stress on dry matter and harvest index is investigated separately. The applied changes have led to the development of the following Eq. in this model:

$$B = WP \sum Tr \tag{1}$$

$$Y = HI \times B \tag{2}$$

where *WP* is water productivity (in units of kg (biomass) m<sup>-2</sup> (land area) mm<sup>-1</sup> (water transpired)) and *Tr* is plant transpiration (mm).

**Table 1** Characteristics of the main crops of the Moghan irrigation network in 2020

Crop characteristics	Units	Wheat	Maize_1	Maize_2	Soybean	Alfalfa
<i>A</i>	(ha)	1495	585	882	280	155
<i>Y<sub>max</sub></i>	(Kg ha <sup>-1</sup> )	6500	9800	7200	3800	15,000
<i>Y<sub>ave</sub></i>	(Kg ha <sup>-1</sup> )	4200	7400	5000	2500	12,000
<i>P</i>	(RI Kg <sup>-1</sup> )	36,400	36,000	36,000	56,000	25,000
<i>C</i>	(RI 10 <sup>4</sup> ha <sup>-1</sup> )	3200	4050	3750	3440	3570
<i>P<sub>w</sub></i>	(RI ha <sup>-1</sup> )	4,586,400	7,992,000	5,400,000	4,200,000	8,975,520

*A* cultivated area, *Y<sub>max</sub>* maximum crop yield, *Y<sub>ave</sub>* average crop yield, *P* market price in Rial, *C* production cost, *P<sub>w</sub>* water charge in the network, 1:Spring, 2: Summer

### AquaCrop Plug-in Program

FAO has developed the AquaCrop plug-in program, whose calculation methods are similar to the standard AquaCrop program (Raes et al., 2012). It provides the simulation possibility without a user interface. The plug-in program runs consecutive projects and saves each project’s simulation results (daily, 10-day, monthly, and quarterly) of each project in an output file that includes information about the simulation period, climate, soil, and water balance, and crop yield. (Raes et al., 2012). The plug-in program makes it possible to include the AquaCrop model in other programs and makes consecutive runs possible without a user interface. The AquaCrop plug-in version 6.0 was used in this research.

In this study, the AquaCrop model was run for each crop in net irrigation requirement mode to find the potential crop yields. The agricultural year was divided into 36 periods of 10 days to allocate water to the different crops. The potential yield and the corresponding amount of water calculated from the model simulation were then entered into the optimization model. The optimization code (i.e., AquaCrop plug-in for irrigation scheduling) uses a specified irrigation depth based on the water content at field capacity and irrigation time based on the irrigation interval (Generation of irrigation schedule). There are some studies in the Moghan Plain for the calibration and validation of the AquaCrop model for important crops (Adabi et al., 2020; Izadfard et al., 2021). In this research, to determine the calibration parameters for the main cultivated crops in the study area, the results of Izadfard et al. (2021) were used. The calibrated parameters are shown in Table 2. For forage crops such as alfalfa, the average effect of cuttings in the growing season was considered. A standard crop coefficient curve was considered, in which only a single value for crop coefficient mid needs to be employed for the whole growing season (Allen et al., 1998).

**Table 2** AquaCrop model calibration parameters for the main cultivated crops in the study area (Izadfard et al., 2021)

Crop parameters	Unit	Wheat	Maize_1	Maize_2	Soybean	Alfalfa
<b>Growth factors</b>						
Base temperature	°C	0	8	8	5	0
Cut-off temperature	°C	26	30	30	30	30
Crop water productivity	g/m <sup>2</sup>	15	33.7	33.7	15	17
Expansion upper threshold	–	0.2	0.14	0.14	0.15	0.2
Expansion lower threshold	–	0.65	0.72	0.72	0.65	0.7
<b>Morphologic factors</b>						
Initial canopy cover	%	6.75	0.49	0.49	0.1	1.8
Maximum canopy cover	%	88	89	89	77	87
Canopy growth coefficient	%/day	3.9	12.7	12.7	13.6	21.9
Canopy decline coefficient	%/GDD	0.38	0.56	0.56	0.15	0.8
Maximum root depth	m	1.5	2.3	2.3	2	1.5
<b>Phenology factors</b>						
Growing degree days required to emergence	GDD	150	96	120	162	-
Growing degree days required to reach full canopy	GDD	1203	901	766	998	75
Growing degree days required to reach senescence	GDD	1704	1664	1443	1609	362
Growing degree days required to reach harvest	GDD	2414	2165	1723	2001	376
<b>Planting and harvest factors</b>						
Harvest index	%	48	48	48	40	85

## Objective Function and Decision Variables

The optimal irrigation water management was carried out in the IAU under different water requirements conditions on a ten-day scale. The decision variables in this model were the amount of irrigation water depth in each of the 36 periods as well as the crop cultivation area. Equation 3 represents the *EB* for each crop:

$$\begin{aligned}
 EB &= \text{benefit per crop per hectare} \\
 &= (\text{crop sales per hectare} - \text{costs per hectare}) \quad (3) \\
 &= (Y_i \times P_i) - (C_i + P_w \times IR_i)
 \end{aligned}$$

where  $Y_i$  is the yield of crop  $i$  (kg/ha),  $P_i$  is the market price (Rial/kg),  $C_i$  represents production cost (Rial/ha),  $P_w$  is water charge (Rial/m<sup>3</sup>) and  $IR$  is irrigation depth (mm). The meaning of the production costs is: land preparation, planting, cultivating and harvesting. These costs are different for each product and for each agricultural year. The amount of  $IR$  is calculated by dividing the net irrigation depth by the irrigation efficiency ( $IR = NIR/E$ ). In Eq. 4, the *EB* function for the crop pattern is shown:

$$EB = \left( \sum_{i=1}^n A_i \times (Y_i \times P_i - C_i - P_w \times NIR_i/E) \right) \quad (4)$$

where  $NIR_i$  is net irrigation depth (mm),  $E$  is irrigation efficiency, and  $A_i$  is the cultivated area (ha). Water allocation in this model was performed to maximize the IAU's *EU* for

five main crops. The selected option for the objective function was assumed to include the drainage water salinity as a penalty factor in the total benefit and the effect of soil water salinity as a factor in each crop's benefit. Therefore, considering the soil water salinity and drainage water salinity, the *EU* function can be calculated as follows,

$$EU = \alpha' \left( \sum_{i=1}^n \gamma_i \times A_i \times (Y_i \times P_i - C_i - P_{wi} \times NIR_i/E) \right) \quad (5)$$

The coefficient  $\gamma$  represents changes in benefit due to the soil water salinity effects, and  $\alpha'$  is a coefficient to consider the effect of drained water salinity in the total benefit. By applying these coefficients, the benefit obtained will not be the net benefit of that year, but the long-term environmental effects are also considered.

## Conditions Governing the Optimization Model

Using the optimization model, the appropriate combination of cultivation is selected among the common crops of the region. The crops' sowing date, harvest date, total cost, and market price are entered into the optimization model. The following constraints limit the optimization:

1- The total cultivated area of different crops in each period should not exceed the area of arable land in the region (Eq. 6).

$$\sum_{i=1}^i A_{i,d} \leq AT \tag{6}$$

where  $A_{i,d}$ , and  $AT$  are the cultivated area of crop  $i$  in period  $d$  and the total area of arable land in the region.  $d$  is considered to be ten days in this study.

2- A mild water deficit is optimal and can reduce water consumption without reducing yield (Wang et al., 2022). In this study, deficit irrigation of less than 25% and over-irrigation of more than 25% (to meet the leaching requirement) were prohibited. The net irrigation depth variation was limited to:

$$0.75 \times NetIrri_{id} \leq NIR_{id} \leq 1.25 \times NetIrri_{id} \tag{7}$$

where,  $NetIrri_{i,d}$  and  $NIR_{i,d}$  are, the crop irrigation requirement and the irrigation depth for crop  $i$  in period  $d$ .

3- The total volume of irrigation water used for crops in each period should not exceed the available water volume in that period (Eqs. 8 and 9).

$$V_d = \sum_{i=1}^i IR_{i,d} \times A_i \tag{8}$$

$$V_d \leq W_d \tag{9}$$

where  $IR_{i,d}$ , and  $V_d$  are the depth of gross irrigation water for plant  $i$  in period  $d$  and the total volume of water used for all crops in period  $d$ .  $W_d$  is the volume of available irrigation water in period  $d$ .

4- The discharge of drainage water should not lead to an increase in the salinity of the river water more than the permissible limit. Drained water volume and salinity for each crop can be derived from AquaCrop outputs. Thus, the salt amount coming from certain irrigation for each period of IAU which enters the river can be obtained from the average cultivated crops' salinity in that period (Eq. 10). Furthermore, the river water salinity at output location in a certain period before the entrance of drainage water and its volume is available. Therefore, the river water salinity after the entrance of the drained water derives as follows:

$$EC_{drain_d} = \frac{\sum_{i=1}^i EC_{drain_{i,d}} \times V_{drain_{i,d}}}{\sum_{i=1}^i V_{drain_{i,d}}} \tag{10}$$

$$EC_{river_d} - mod = \frac{(EC_{river_d} \times V_{river_d}) + (EC_{drain_d} \times V_{drain_d})}{V_{river_d} + V_{drain_d}} \tag{11}$$

In these equations,  $EC_{drain_d}$  is the average electrical conductivity of the drained water in period  $d$ ,  $EC_{river_d} - mod$  represents the river  $EC$  after receiving the drained water,  $EC_{drain_{i,d}}$  is the contribution of crop  $i$  to the salinity

of drained water in period  $d$ ,  $V_{drain_{i,d}}$  is the volume of the drained water due to irrigation of crop  $i$ ,  $EC_{river_d}$  is the salinity of the river at the outlet before receiving drained water,  $V_{river_d}$  is the volume of the river water in period  $d$  at the outlet before receiving drained water, and  $V_{drain_d}$  is the total drained volume in period  $d$ . To consider the drained water salinity as a penalty factor in the benefit, the coefficient  $C$  is calculated every day by Eq. 12.

$$C = \frac{EC_{river_d} - mod - EC_{river}}{EC_{river}} \tag{12}$$

In case the river water salinity after the entrance of the drainage water is lower than the river water salinity at the output location before the entrance of drainage water,  $C$  is lower than or equal to zero. In such cases, there is no need to apply a punishment coefficient ( $\alpha'$ ) (i.e.,  $\alpha'$  equals one). In contrast, if the entered drainage water increases the river water salinity,  $C$  exceeds zero, and  $\alpha'$  can be applied. Moreover, the punishment coefficient intensifies according to the salinity increment. The  $\alpha'$  is calculated daily, and an average yearly coefficient applies to the objective function.  $\alpha'$  values for the Moghan region were derived based on local experts' observations and suggestions, as shown in Table 3. Noteworthy,  $\alpha'$  regional coefficients can be modified depending on the initial river water salinity and its environmental effects.

5- Cultivation should not drastically affect soil salinity in the root zone to achieve sustainable agriculture and maintain soil quality. Therefore, in this study, the soil water salinity coefficient ( $\gamma$ ) was determined by multiplying two salinity change coefficients in the range of in-class coefficient ( $\gamma_1$ ) and the class change coefficient ( $\gamma_2$ ) (Eq. 13). If initial soil salinity ( $EC_{so}$ ) and soil water salinity after irrigation of plant  $i$  ( $EC_{swi}$ ) are known (which are outputs of the AquaCrop model), salinity classes are also considered based on the Wilcox diagram (Table 5), and each class changes between  $EC_{min}$  and  $EC_{max}$ ,  $\gamma_1$  and  $\gamma_2$  can be obtained from Table 4. It should be mentioned that the coefficient within the class is applied exponentially (Table 5).

$$\gamma = \gamma_1 \times \gamma_2 \tag{13}$$

If the soil water salinity at the end of the irrigation equals the initial soil water salinity,  $\gamma_1$  equals one. If the

**Table 3** Suggested values for determining the  $\alpha'$  coefficient

$\alpha$	$C$
1	$\leq 0$
0.95	0–0.1
0.85	0.1–0.3
0.7	0.3–0.7
0.5	0.7 <

**Table 4** Classification of soil water salinity coefficients (ds m<sup>-1</sup>)

Class change coefficient		In-class		Changes
$\gamma_2$	Criteria for applying the coefficient	$\gamma_1$	Criteria for applying the coefficient	
0.5	$EC_{sw_i} > EC_{max}$	0.5–1	$EC_{sw_i} - EC_{So} > 0$	Increase in salinity
1	$EC_{min} < EC_{sw_i} < EC_{max}$	1	$EC_{sw_i} - EC_{So} = 0$	Unchanged
1.5	$EC_{sw_i} < EC_{min}$	1.1	$EC_{sw_i} - EC_{So} < 0$	Decrease in salinity

**Table 5** Salinity classes to determine the  $\gamma$  coefficient (Wilcox, 1955)

$EC_{max}$ (ds m <sup>-1</sup> )	$EC_{min}$ (ds m <sup>-1</sup> )	Class
0.25	0	Very good
0.75	0.25	Good
2.25	0.75	Medium
>	2.25	Unsuitable

soil water salinity at the end of the irrigation exceeds the initial soil water salinity,  $\gamma_1$  is considered lower than one, and vice versa. Furthermore, if the amount of reduction or increase in the soil water salinity in the root zone after the end of the irrigation does not exceed  $EC_{min}$  and  $EC_{max}$  of the Wilcox index,  $\gamma_2$  equals one, which shows no change in the soil salinity class. Otherwise,  $\gamma_2$  is considered lower ( $EC_{sw_i} > EC_{max}$ ) or higher than one ( $EC_{sw_i} < EC_{min}$ ), which leads to a change in the soil salinity class.  $\gamma_1$  and  $\gamma_2$  values for the Moghan region were suggested in Table 4 based on an engineering judgment. Undoubtedly these values could be enhanced with more experience and based on economic evaluations.

Applying these coefficients ( $\gamma_1$  and  $\gamma_2$ ) to the objective function accounts for the crop cultivation effects on production stability and long-term benefit. To this end, an increase in soil salinity destabilizes the production and reduces the long-term benefit while a reduction in soil salinity improves the production stability and long-term benefit (although it may not affect the current year's benefit).

### Genetic Optimization Algorithm

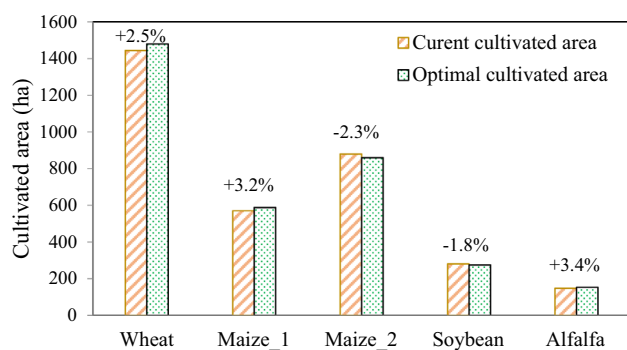
Researchers developed algorithms to optimize any alternative issue in the agriculture (Osroosh et al., 2016), being stochastic or deterministic among the most accepted algorithms. The evolutionary algorithms allow changing a result to change until receiving the optimal solution by seeking a process that simulates living beings in nature, such as genetic algorithms (Villacampa et al., 2019). Since AquaCrop software is needed to calculate the crop yield without any provided formula, it is not feasible to use the optimization software and solve the mathematical model. Genetic algorithm has been used in many studies to generate irrigation data and crop area (Guo et al., 2021; Rabie

et al., 2015; Shen et al., 2021). Hence, in this research, the genetic algorithm optimization method was used to allocate water to crops in the Moghan network. A genetic algorithm is one of the intelligent methods for optimization problems. This algorithm is based on repetition. In this method, a set of decision variables or chromosomes that are effective on the objective function forms the initial population (possible solutions). Maintaining genetic operators such as selection, cross and mutation on the decision variables of the initial population leads to the production of a more competent generation. This process is repeated in different generations (Goldberg, 1989). Thus, members or better solutions evolve over generations. Then, based on the value of the objective function, it categorizes the best answers among the answers in the form of the new generation. This process is repeated until a new generation is not produced. The produced irrigation data is used as an input to AquaCrop, and the crops' yield is derived as an output from the model. In addition to the yield, drainage water salinity for each crop is also calculated by AquaCrop. To this end, C# coding was done in Visual Studio.

## Results and Discussion

### Water Optimal Allocation

The optimal cultivated area of the studied crops was obtained by running the optimization program. Figure 5 shows the cultivated area of the IAU in the current conditions compared to the optimal allocation conditions. The numbers in the figure demonstrate the difference between the existing cultivated crop areas compared to the optimal allocation conditions. The model prioritized crops with more *EU* and less water requirement than other crops by reducing costs and complying with restrictions. In the optimal cropping pattern, the cultivated areas of wheat, first-cultivation maize, and alfalfa have increased by 2.5%, 3.2%, and 3.4%, respectively, compared to the initial cultivated area. Among the crops, wheat requires less water than other crops, whereas first-cultivation maize and alfalfa have a higher water requirement. Their cultivation area has increased more due to their higher yield and, as a result, greater economic



**Fig. 5** Comparison of the existing and optimal cultivated area of the Moghan irrigation network crops

**Table 6** Comparison of the crops allocated water depth in normal and optimal conditions

Crop	Normal allocated water depth (mm/ha)	Optimal allocated water depth (mm/ha)	Reduction (%)
Wheat	678	541	20
Maize_1	1110	1004	10
Maize_2	900	794	12
Soybean	926	790	15
Alfalfa	2074	1580	24
Sum	5688	4709	17

value than the other crops. The cultivated areas of second-cultivation maize and soybean experienced a reduction of 2.3 and 1.8 percent.

The AquaCrop model was run for each crop in the net irrigation water requirement mode. Therefore, the maximum crop yield and the water depth calculated from the implementation of this model were considered normal conditions. Table 6 compares the allocated crops' water depth in two normal and optimal conditions. According to Table 6, the allocated water depth in the optimal conditions for all crops is lower than the allocated water depth in the normal conditions. The highest percentage of reduction in the allocated water depth is related to the alfalfa by 24%, and the lowest is related to the first-cultivation maize by 10%. A fraction of the first-cultivation maize's water requirement, during the growing season, is supplied with rainfall. Alfalfa, a crop that grows and develops throughout the year, has received less water than other crops. For all the investigated crops, the allocated water depth in the optimal condition compared to the normal condition has saved water consumption by 17%. The optimal distribution of water in different growth periods of each crop is shown in Fig. 6. The model can run a deficit irrigation of less than 25% and an over-irrigation of less than 25%. For soybean (Fig. 6d), first-cultivation maize

(Fig. 6b), and second-cultivation maize (Fig. 6c), the optimal water depth distribution in the entire growth stages has been less than the normal water depth. However, for the wheat (Fig. 6a) in the 34th and 35th growth stages (the last ten days of February and the first ten days of March), 7 and 17% over-normal water were considered. For the alfalfa (Fig. 6e) in the fourth growth stage (last ten days of April), 15% over-normal was considered. Since in the previous irrigation periods, the optimum water depth was lower than the normal water depth, it caused a decrease in the soil moisture content in the root zone. Therefore, to compensate water content, the model has chosen over-irrigation, which, in addition to compensating the soil moisture, it also helps to leaching. In the remains of the growth stages of wheat and alfalfa, the optimal water depth distribution was lower than the normal water depth.

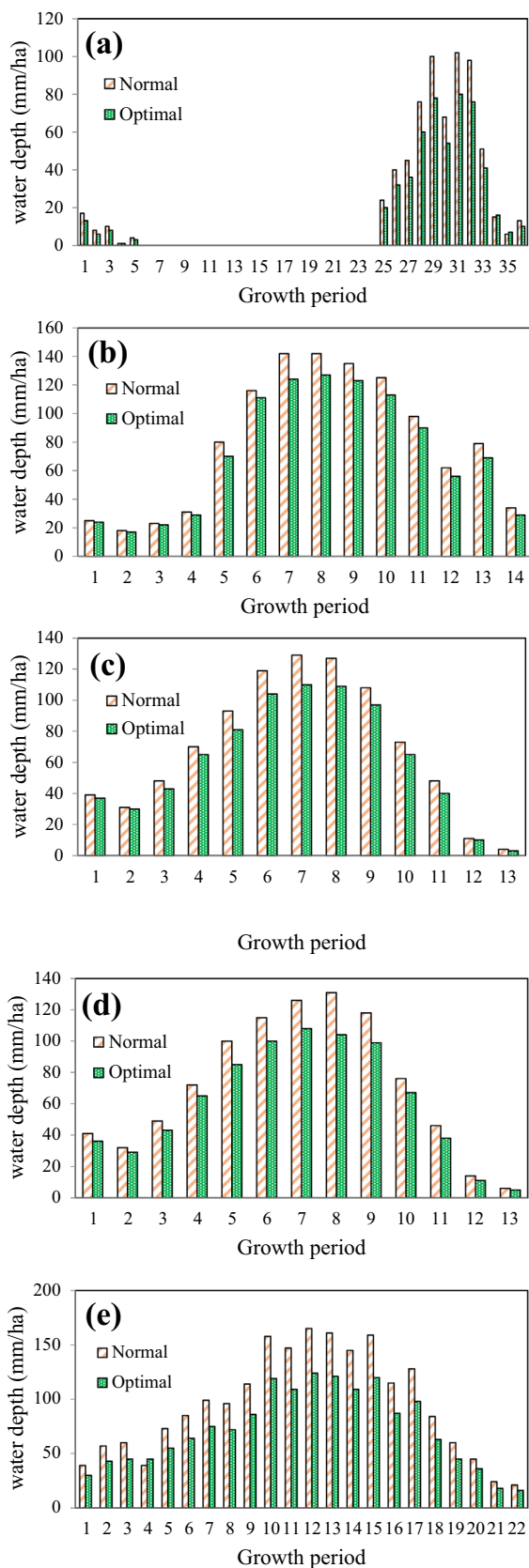
## EB

The volume of water consumed by the IAU and the amount of *EB* for two normal and optimal conditions are given in Table 7. In the conditions of optimal water allocation, the volume of allocated water decreases by 14.7%, while *EB* increases by only 5.7%. Therefore, the optimal water allocation in this area encourages saving water consumption more than increasing benefit. Saving water consumption causes a slight increase in *EB* due to the small water charge in the Moghan network. As a result, water users consider water a worthless commodity and use it without economic considerations. Meanwhile, if the correct price for water is determined, the *EB* will increase to a greater extent. The former researchers' findings have shown that a water charge is an important option for saving water for farmers (Chu and Grafton., 2020). Also, if the water charge is set correctly, the farmers will be sensitive to it (Huang et al., 2010). The study by Cortignani and Severini (2009), conducted in Italy, showed that increasing water charges by 200 and 300 percent and applying five to ten percent water reduction policies are effective in reducing water consumption.

## Water Productivity

Table 8 shows the potential crop yield values after optimization and the water productivity for each crop. The results indicate that the water productivity index has increased after optimization for all crops. Alfalfa has the most significant increase in water productivity (by 35%), with a 24% decrease in the allocated water depth. Kanooni (2013) also presented similar results for the current study area.





**Fig. 6** Comparison of normal and optimal water depth distribution in growth stages of wheat (a), first-cultivation maize (b), second-cultivation maize (c), soybean (d), and alfalfa (e)

**Table 7** Comparison of the *EB* and the volume of water consumed in normal and optimal conditions

	Normal	Optimal	Change (%)
<i>EB</i> (RI 10 <sup>6</sup> )	747,805	790,821	+ 5.7
<i>V</i> (M m <sup>3</sup> )	29.7	25.33	- 14.7

**Table 8** Water productivity values in normal and optimal conditions

Water Productivity				
Crop	Yield	Normal	Optimal	Increase
	Kg ha <sup>-1</sup>	RI m <sup>-3</sup>	RI m <sup>-3</sup>	%
Wheat	6640	34,360	44,675	30
Maize_1	10,166	31,427	36,452	16
Maize_2	7130	27,600	32,327	17
Soybean	3700	21,771	26,228	20
Alfalfa	15,350	17,839	24,222	35

**Table 9** Salinity of soil water after completion of irrigation for studied crops

Crop	Wheat	Maize_1	Maize_2	Soybean	Alfalfa
<i>EC<sub>SW</sub></i> (ds/m)	1.82	1.91	2.02	2.01	1.8
$\gamma_1$	1	0.9	0.9	0.9	1
$\gamma_2$	1	1	1	1	1
<i>EC<sub>So</sub></i> = 1.8 ds/m					

**The Effect of Soil Water Salinity Coefficient on EU**

It has been shown that the AquaCrop model could be a feasible tool to predict the soil salinity change trend (Mohammadi et al., 2016; Pourgholam-Amiji et al., 2021). The soil water salinity values (*EC<sub>SW</sub>*) after the completion of irrigation of each crop, which are the outputs of the AquaCrop model in the optimization model, are presented in Table 9. Based on detailed soil studies, the studied area has different types of soils. However, according to the detailed soil science report of the canal area, the dominant soil of the Pars-Abad series has a salinity of 1.8 ds/m, which is placed in the medium class of salinity (Table 5), according to Wilcox's classification. The results of Table 9 indicate that the soil water salinity for first and second-cultivation maize and soybean after the completion of irrigation has increased from the initial soil salinity. However, this value did not exceed the maximum salinity of the Wilcox classification. Therefore, the coefficient of change of class  $\gamma_2$  (Table 4) equals 1. For the wheat, due to the insignificant difference between the initial soil salinity and soil water salinity after irrigation (the difference is less than 0.1), the value of the in-class coefficient ( $\gamma_1$ ) and class change ( $\gamma_2$ ) is equal to 1. The

**Table 10** *EB* and *EU* for the studied crops

Crop	<i>EB</i> ( $\times 10^6$ RI)	$\gamma$	<i>EU</i> (excluding $\alpha'$ )	$\alpha'$	<i>EU</i>
Wheat	310,345	1	310,345		
Maize_1	191,376	0.9	172,238		
Maize_2	188,491	0.9	169,642	0.97	
Soybean	47,519	0.9	42,767		
Alfalfa	53,091	1	53,091		
Sum	790,821		748,083		725,640

crop yield and soil salinity could be significantly affected by rainfall conditions (Liu et al., 2019; Zhai et al., 2022). In the study area, during the growth period of crops such as wheat and the first-cultivation maize, rainfall distribution is higher, and crops obtain part of their water requirement from rainfall. During the summer season, rainfall is reduced, and the crops' rainwater usage, such as second-cultivation maize and soybeans, which are part of their growth period in summer, is reduced. For alfalfa, the soil water salinity after irrigation is equal to the initial soil salinity, so for this crop, both the in-class coefficient ( $\gamma_1$ ) and class change coefficient ( $\gamma_2$ ) are equal to 1. Crops such as developed alfalfa that have extensive roots can be beneficial in lowering the average salinity in the root zone (Minhas & Gupta, 1993; Hanks et al., 1990). The roots of an established alfalfa can extend to a depth of 2.5 m (Vaughan et al., 2002). Therefore, the results indicate that, except for alfalfa and wheat, inappropriate crop rotation and neglect of soil salinity management (e.g., using certain fertilizers to prevent and eliminate soil salinity) increase the soil salinity over time. (The values of the soil water salinity coefficient ( $\gamma$ ) for all the studied crops are given in Table 10).

## EU

Table 10 presents the obtainable *EB* for each crop, the obtainable total *EB* for the entire IAU, and the amount of IAU's *EU*. The results show that the IAU's *EB* is equal to 790,821 million Rials. For wheat and alfalfa, the amount of *EU* (excluding  $\alpha'$ ) is equal to the amount of *EB*, but the amount of *EU* (excluding  $\alpha'$ ) for the first and second-cultivation maize and soybeans is 10% is lower than the value of *EB*. The reason for this reduction is the increase of soil salinity in the root zone due to the irrigation of these crops. The annual average value of  $\alpha'$  coefficient was calculated as 0.97. The value of  $\alpha'$  less than 1 indicates that the inflow of drained water produced by the IAU will enter the Aras River in the long term, increasing the river water's salinity. By applying the  $\alpha'$  coefficient as a penalty factor in the total benefit, the *EU* value of the IAU was reduced by 8.2% compared to *EB*. Resultantly, the combination of planting the studied crops will be beneficial for the farmers in the same growing season, but in case of choosing incompatible

plants for the local climate, and not considering the proper measures to prevent soil salinity and river water salinity, the *EU* of the IAU decreases. Furthermore, the *EU* can be increased by planting crops such as alfalfa and wheat, which reduce soil water salinity.

## Conclusions

Sustainable agriculture should be environmentally compatible with nature and economically beneficial, and this benefit should continue in the long term. In this regard, optimization models are valuable tools that not only increase benefits but also assess the feasibility of extending the cultivation area and can be used for economic analyses. Therefore, in this study, a combination of the AquaCrop plug-in model with the genetic algorithm optimization model was used for the optimal water allocation in the Moghan irrigation network. The objective function in this study was set to maximize the *EU* heuristic function instead of the *EB* function. The results indicated that the allocated water depth to the IAU decreased by 17% in the optimal condition compared to the normal condition while the water productivity increased after optimization for all crops. Alfalfa had the highest increase in water productivity compared to other crops by reducing the allocated water depth by 24%, followed by wheat with a 20% reduction. The values of soil water salinity coefficient ( $\gamma$ ) showed that in case of mismanagement in soil salinity prevention, maize and soybeans increase soil salinity in the long term. The  $\alpha'$  coefficient of 0.97 indicated that the combination of five major crop cultivation in this area increases the river water salinity in the long term. By applying all two mentioned coefficients, the *EU* value in the IAU was reduced by 8.2% compared to *EB*. Therefore, using the proposed *EU*, it is possible to identify crops that reduce soil salinity and river water salinity, and not only *EB* but also *EU* is increased. The result of this study can be used by the network managers for selecting the best crop pattern in a network scale. Utilizing this approach can protect the country's limited water resources to obtain sustainable agriculture.

**Data Availability** The data that support this study will be shared upon reasonable request to the corresponding author.

## Declarations

**Conflict of interest** The authors declare no conflicts of interest.

## References

- Adabi, V., Azizian, A., Ramezani Etedali, H., Kaviani, A., & Ababaei, B. (2020). Local sensitivity analysis of AquaCrop model for wheat and maize in qazvin plain and Moghan Pars-Abad in Iran. *Iran J Irrig Drain*, 6(13), 1565–1579.

- Alizade Govarchin, G. Y., Baykara, M., & Unal, A. (2017). Analysis of decadal land cover changes and salinization in Urmia Lake Basin using remote sensing techniques. *Nat Hazards Earth Syst Discuss.* <https://doi.org/10.5194/nhess-2017-212>
- Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration: guidelines for computing crop water requirements FAO Irrigation and drainage paper* (pp. 1–300). Rome: FAO.
- Bastiaanssen, W. G., Allen, R. G., Droogers, P., D'Urso, G., & Steduto, P. (2007). Twenty five years modeling irrigated and drained soils: State of the art. *Agricult Water Manag*, 92(3), 111–125. <https://doi.org/10.1016/j.agwat.2007.05.013>
- Chu, L., & Grafton, R. Q. (2020). Water pricing and the value-add of irrigation water in Vietnam: Insights from a crop choice model fitted to a national household survey. *Agricult Water Manag*, 228, 105881. <https://doi.org/10.1016/j.agwat.2019.105881>
- Connor, J. D., Schwabe, K., King, D., & Knapp, K. (2012). Irrigated agriculture and climate change: the influence of water supply variability and salinity on adaptation. *Ecological Economics*, 77, 149–157. <https://doi.org/10.1016/j.ecolecon.2012.02.021>
- Cortignani, R., & Severini, S. (2009). Modeling farmlevel adoption deficit irrigation using positive mathematical programming. *Agricult Water Manag*, 96(12), 1785–1791.
- Doorenbos, J., & Kassam, A. H. (1979). *Yield response to water. FAO irrigation and drainage paper 33*. Rome: FAO.
- Douaik, A., Van Meirvenne, M., & Toth, T. (2006). Temporal stability of spatial patterns of soil salinity determined from laboratory and field electrolytic conductivity. *Arid Land Research and Management*, 20(1), 1–13. <https://doi.org/10.1080/15324980500369392>
- García-Vilaa, M., & Fereres, E. (2012). Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. *Euro J Agron*, 36(1), 21–31. <https://doi.org/10.1016/j.eja.2011.08.003>
- Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley-Longman, Publishing Co Inc.
- Guo, D., Olesen, J. E., Manevski, K., & Ma, X. (2021). Optimizing irrigation schedule in a large agricultural region under different hydrologic scenarios. *Agricult Water Manag*, 245, 106575. <https://doi.org/10.1016/j.agwat.2020.106575>
- Hanks, R. J., Dudley, L. M., Cartee, R. L., Mace, W. R., Pomela, E., Kidman, R. L., & McCurdy, G. D. (1990). Use of saline waste water from electrical power plants for irrigation. 1989 report. Part 1. Utah Agricultural Experiment Station, 133.
- Huang, Q., Rozelle, S., Howitt, R., Wang, J., & Huang, J. (2010). Irrigation water demand and implications for water pricing policy in rural China. *Environ Develop Econ*, 15(3), 293–319. <https://doi.org/10.1017/S1355770X10000070>
- Izadfar, A., Sarmadian, F., Jahansooz, M. R., & Asadi Oskouei, E. (2021). Optimum cropping pattern based on irrigation water productivity using AquaCrop simulation model. *J Agricult Sci Technol*, 23(5), 1163–1178.
- Jahin, H. S., Abuzaid, A. S., & Abdellatif, A. D. (2020). Using multivariate analysis to develop irrigation water quality index for surface water in Kafr El Sheikh Governorate Egypt. *Environ Technol Innovat*, 17, 100532. <https://doi.org/10.1016/j.eti.2019.100532>
- Kanooni, A. (2013). Development of an Integrated Optimal Water Allocation and Distribution Model at Different Levels of Irrigation Networks. Ph.D. thesis. Tehran: Tarbiat Modares University, Department of water structures engineering, (In Persian) pp. 177.
- Kanooni, A., & Monem, M. J. (2014). Integrated stepwise approach for optimal water allocation in irrigation canal. *Irrigation and Drainage*, 63, 12–21. <https://doi.org/10.1002/ird.1798>
- Kheir, A. M., Alkharabsheh, H. M., Seleiman, M. F., Al-Saif, A. M., Ammar, K. A., Attia, A., Zoghdan, M. G., Shabana, M. M. A., Aboelsoud, H., & Schillaci, C. (2021). Calibration and validation of AQUACROP and APSIM models to optimize wheat yield and water saving in arid regions. *Land*, 10(12), 1375. <https://doi.org/10.3390/land10121375>
- Kumar, V., & Yadav, S. M. (2019). Optimization of cropping patterns using elitist-Jaya and elitist- TLBO algorithms. *Water Resour Manag*, 33(5), 1817–1833. <https://doi.org/10.1007/s11269-019-02204-z>
- Li, J., Jiao, X., Jiang, H., Song, J., & Chen, L. (2020). Optimization of irrigation scheduling for maize in an arid oasis based on simulation–optimization model. *Agronomy*, 10(7), 935. <https://doi.org/10.3390/agronomy10070935>
- Li, J., Song, J., Li, M., Shang, S., Mao, X., Yang, J., & Adeloje, A. J. (2018). Optimization of irrigation scheduling for spring wheat based on simulation–optimization model under uncertainty. *Agricult Water Manag*, 208, 245–260. <https://doi.org/10.1016/j.agwat.2018.06.029>
- Linker, R., Ioslovich, I., Sylaios, G., Plauborg, F., & Battilani, A. (2016). Optimal model-based deficit irrigation scheduling using AquaCrop: a simulation study with cotton, potato and tomato. *Agricult Water Manag*, 163, 236–243. <https://doi.org/10.1016/j.agwat.2015.09.011>
- Liu, B., Wang, S., Kong, X., Liu, X., & Sun, H. (2019). Modeling and assessing feasibility of long-term brackish water irrigation in vertically homogeneous and heterogeneous cultivated lowland in the North China Plain. *Agricult Water Manag*, 211, 98–110.
- Martinez-Romero, A., Lopez-Urrea, R., Montoya, F., Pardo, J. J., & Dominguez, A. (2021). Optimization of irrigation scheduling for barley crop, combining AquaCrop and MOPECO models to simulate various water-deficit regimes. *Agricult Water Manag*, 258, 107219. <https://doi.org/10.1016/j.agwat.2021.107219>
- Mathur, Y. P., Sharma, G., & Pawde, A. W. (2009). Optimal operation scheduling of irrigation canals using genetic algorithm. *Int J Recent Trends Eng*, 1(6), 11–15.
- McBride, G. B. (2002). Calculating stream reaeration coefficients from oxygen profiles. *Journal of Environmental Engineering*, 128(4), 384–386. [https://doi.org/10.1061/\(ASCE\)0733-9372\(2002\)128:4\(384\)](https://doi.org/10.1061/(ASCE)0733-9372(2002)128:4(384))
- Minhas, P. S., & Gupta, R. K. (1993). Conjunctive use of saline and non-saline waters. I. Response of wheat to initial salinity profiles and salinization patterns. *Agricult Water Manag*, 23, 125–137. [https://doi.org/10.1016/0378-3774\(93\)90036-A](https://doi.org/10.1016/0378-3774(93)90036-A)
- Mohammadi, M., Ghahraman, B., Davary, K., Ansari, H., Shahidi, A., & Bannayan, M. (2016). Nested validation of aquacrop model for simulation of winter wheat grain yield, soil moisture and salinity profiles under simultaneous salinity and water stress. *Irrigation and Drainage*, 65, 112–128.
- Monem, M. J., & Namdariyan, R. (2005). Application of Simulated Annealing (SA) Techniques for Optimal Water Distribution in Irrigation Canals. *Irrigation and Drainage*, 54(4), 365–373. <https://doi.org/10.1002/ird.199>
- Nemoto, Y., & Sasaki, T. (2002). Differential stress responses of early salt stress responding genes in common wheat. *Phytochemistry*, 61(2), 129–133. [https://doi.org/10.1016/S0031-9422\(02\)00228-5](https://doi.org/10.1016/S0031-9422(02)00228-5)
- Oad, R., Garcia, L., Kinzli, K. D., Patterson, D., & Shafike, N. (2009). Decision support systems for efficient irrigation in the Middle Rio Grande Valley. *Journal of Irrigation and Drainage Engineering*, 135(2), 177–185. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2009\)135:2\(177\)](https://doi.org/10.1061/(ASCE)0733-9437(2009)135:2(177))
- Osroosh, Y., Peters, R. T., Campbell, C. S., & Zhang, Q. (2016). Comparison of irrigation automation algorithms for drip-irrigated apple trees. *Comput Electron Agricult*, 128, 87–99. <https://doi.org/10.1016/j.compag.2016.08.013>
- Pourgholam-Amiji, M., Liaghat, A., Ghameshlou, A. N., & Khoshravesh, M. (2021). The evaluation of DRAINMOD-S and AquaCrop models for simulating the salt concentration in soil

- profiles in areas with a saline and shallow water table. *Journal of Hydrology*, 598, 126259.
- Quinn, N. W. (2011). Adaptive implementation of information technology for real-time, basin-scale salinity management in the San Joaquin Basin, USA and Hunter River Basin Australia. *Agricult Water Manag*, 98(6), 930–940. <https://doi.org/10.1016/j.agwat.2010.11.013>
- Rabie, Z., Honar, T., & Bateni, M. (2015). Determination of optimal and water allocation under limited water resources using soil water balance in ordibeheht canal of doroodzan water district. *Iran Agricult Res*, 34(2), 21–28. <https://doi.org/10.22099/IAR.2016.3454>
- Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. (2012). Reference Manual: AquaCrop (Version 4.0). *FAO Land and Water Division, Rome, Italy* (pp. 1–164). <http://www.fao.org/nr/water/aquacrop.html>. Accessed Nov 2013
- Rath, A., Samantary, S., Biswal, S., & Swain, P. C. (2018). Application of genetic algorithm to derive an optimal cropping pattern, in part of Hirakud command. *Progress in computing, analytics and networking: proceedings of ICCAN 2017* (pp. 711–721). Singapore: Springer Singapore.
- Sandhu, R., & Irmak, S. (2019). Performance of AquaCrop model in simulating maize growth, yield, and evapotranspiration under rainfed, limited and full Irrigation. *Agricult Water Manag*, 223, 105687. <https://doi.org/10.1016/j.agwat.2019.105687>
- Shen, H., Jiang, K., Sun, W., Xu, Y., & Ma, X. (2021). Irrigation decision method for winter wheat growth period in a supplementary irrigation area based on a support vector machine algorithm. *Comput Electron Agricult*, 182, 106032. <https://doi.org/10.1016/j.compag.2021.106032>
- Somlyody, L., Henze, M., Koncsos, L., Rauch, W., Reichert, P., Shanahan, P., & Vanrolleghem, P. (1998). River water quality modeling: III. Future of the atr. *Water Science and Technology*, 38(11), 253–260. [https://doi.org/10.1016/S0273-1223\(98\)00662-3](https://doi.org/10.1016/S0273-1223(98)00662-3)
- Steduto, P., Hsiao, T. C., Fereres, E., & Raes, D. (2012). *Crop yield response to water. FAO Irrigation and drainage paper 66*. Rome: United Nations FAO.
- Vaughan, L. V., MacAdam, J. W., Smith, S. E., & Dudley, L. M. (2002). Root growth and yield of differing alfalfa rooting populations under increasing salinity and zero leaching. *Crop Science*, 42(6), 2064–2071.
- Villacampa, Y., Navarro-González, F. J., Compañ-Rosique, P., & Satorre-Cuerda, R. (2019). A guided genetic algorithm for diagonalization of symmetric and Hermitian matrices. *Applied Soft Computing*, 75, 180–189. <https://doi.org/10.1016/j.asoc.2018.11.004>
- Wabela, K., Hammani, A., Abdelilah, T., Tekleab, S., & El-Ayachi, M. (2022). Optimization of irrigation scheduling for improved irrigation water management in Bilate watershed, Rift valley Ethiopia. *Water*, 14(23), 3960. <https://doi.org/10.3390/w14233960>
- Wang, H. R., Dong, Y. Y., Wang, Y., & Liu, Q. (2008). Water right institution and strategies of the Yellow River valley. *Water Resour Manag*, 22, 1499–1519. <https://doi.org/10.1007/s11269-008-9239-7>
- Wang, Y., Zhang, H., He, Z., Li, F., Wang, Z., Zhou, C., Han, Y., & Lei, L. (2022). Effects of regulated deficit irrigation on yield and quality of isatis indigotica in a cold and arid environment. *Water*, 14(11), 1798. <https://doi.org/10.3390/w14111798>
- Wilcox, L. V. (1955). Classification and use of irrigation waters (No. 969). US Department of Agriculture, Washington D. C. USA.
- Wilkinson, R. E. (2000). *Plant-Environment Interactions*; Marcel dekker: New York, NY, USA, ISBN 0824703774.
- Yao, W., Ma, X., & Chen, Y. (2019). Optimization of canal water in an irrigation network based on a genetic algorithm: A case study of the north china plain canal system. *Irrigation and Drainage*, 68(4), 629–636. <https://doi.org/10.1002/ird.2345>
- Zhai, Y., Huang, M., Zhu, C., Xu, H., & Zhang, Z. (2022). Evaluation and application of the AquaCrop model in simulating soil salinity and winter wheat yield under saline water irrigation. *Agronomy*, 12(10), 2313. <https://doi.org/10.3390/agronomy12102313>

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.