Optimization of Irrigation Management using Water Cycle Algorithm: A Robust Strategy to Improve Water Use Efficiency

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Abstract

To obtain an optimum irrigation management strategy, reaching lower water applications as well as highest possible yields, can be complex regarding various plant and environmental parameters along with various dominancy of each parameter. For this purpose, the relationship among the input irrigation factors (irrigation interval, water salinity, environment), moderate factors (evapotranspiration, soil salinity, plant parameters, fruit parameters, crop yield) and a response (WUE: water use efficiency) were carefully determined using a structural equation modeling according to the first year of experiments. The relations were improved using the dataset of the second year of experiments. The improved models were then used in two optimization methods, water cycle algorithm (WCA) and genetic algorithm (GA), to determine the best combination of irrigation factors and optimize eggplant cultivation. The structural equation modeling indicated that the irrigation interval negatively impacted WUE with a more dominant effect on plant parameters, while water salinity negatively impacted the WUE with a more dominant effect on soil salinity, crop yield and fruit parameters. Further, a low salinity level will be more important than full irrigation to optimize WUE. WCA appeared that the optimal ranges of irrigation interval and water salinity were 2.13-5.23 day and 0.8-2.21 ds/m cultivated in outdoor cultivation, resulting to optimize evapotranspiration, soil salinity, fruit parameters and crop yield in the ranges of 346.23-738.19 mm, 4.16-9.45 ds/m, 33.81-35.12 cm and 1715.7-2190.8 g/plant, respectively; and thus, increase WUE in the range of 3.08-4.89 g/(plant-mm). WCA and GA presented very close optimal values.

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Dear Editor

The attached letter is about a manuscript entitled "**Optimization of Irrigation Management using Water Cycle Algorithm: A Robust Strategy to Improve Water Use Efficiency** " has been submitted to journal of**Water Resources Research**for consideration for possible publication. The authors wish to contribute to the specialized journal in the area of water research.

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The paper has not been published previously, it is not under consideration for publication elsewhere, and if accepted it will not be published elsewhere in substantially the same form, in English or in any other language, without the written consent of the Publisher.

We hope that you will find the paper interesting and worthwhile to be published by the journal.

Thank you in advanced for your cooperation.

Sincerely yours

Mahmood Mahmoodi-Eshkaftaki

Optimization of Irrigation Management using Water Cycle Algorithm: A Robust Strategy to Improve Water Use Efficiency

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To obtain an optimum irrigation management strategy, reaching lower water applications as well as highest possible yields, can be complex regarding various plant and environmental parameters along with various dominancy of each parameter. For this purpose, the relationship among the input irrigation factors (irrigation interval, water salinity, environment), moderate factors (evapotranspiration, soil salinity, plant parameters, fruit parameters, crop yield) and a response (WUE: water use efficiency) were carefully determined using a structural equation modeling according to the first year of experiments. The relations were improved using the dataset of the second year of experiments. The improved models were then used in two optimization methods, water cycle algorithm (WCA) and genetic algorithm (GA), to determine the best combination of irrigation factors and optimize eggplant cultivation. The structural equation modeling indicated that the irrigation interval negatively impacted WUE with a more dominant effect on plant parameters, while water salinity negatively impacted the WUE with a more dominant effect on soil salinity, crop yield and fruit parameters. Further, a low salinity level will be more important than full irrigation to optimize WUE. WCA appeared that the optimal ranges of irrigation interval and water salinity were 2.13–5.23 day and 0.8–2.21 ds/m cultivated in outdoor cultivation, resulting to optimize evapotranspiration, soil salinity, fruit parameters and crop yield in the ranges of 346.23–738.19 mm, 4.16–9.45 ds/m, 33.81–35.12 cm and 1715.7–2190.8 g/plant, respectively; and thus, increase WUE in the range of 3.08–4.89 g/(plant-mm). WCA and GA presented very close optimal values. Repetition of the experiments for two years and proximity of the optimal values using WCA and GA confirm that the optimum amounts are precise and reliable.

Keywords: Evapotranspiration; Irrigation management; Structural equation modeling; Water cycle algorithm; Water use efficiency.

Nomenclature			
A	Top area of the cylindrical pots (cm^2)	N_F	Num. of fruit
AR^2	Adjusted R^2	P_H	Plant height (cm)
D_p	Drainage water (cm^3)	R^2	Coefficient of determination
EC_e	Soil salinity (ds/m)	R_L	Root length (cm)
ET_c	Evapotranspiration (mm)	RMSEA	Root mean square errors of approximation
F_D	Fruit diameter (cm)	RSM	Response surface methodology
F_L	Fruit length (cm)	SEM	Structural equation modeling
GA	Genetic algorithm	S_D	Stem diameter (mm)
GFI	Goodness of fit index	W	Pot weight (g)
I	Applied water (cm^3)	WCA	Water cycle algorithm
IR^2	Intercepted R^2	WUE	Water use efficiency (g/(plant-mm))
MRM	Multivariate regression modeling	ρ_w	Water bulk density (g/cm)
MSE	Mean squared error	λ	Standardized regression weight

1. Introduction

The water use efficiency (WUE) is an index to quantify the use efficiency of water resources towards crop production, describing the relationship between crop yield and evapotranspiration (ET_c). Under limited water supply conditions, WUE plays a crucial role to screen proper irrigation management. Since last few decades, the WUE level has been enhanced through the breeding of high yielding cultivars and managing the soil resource in an effective way (Abd El-Mageed et al., 2016). To achieve efficient irrigation with minimum percolation, runoff losses and environmental pollution, it is necessary to estimate the consumption use of crops or their ET_c. In order to optimize WUE, some moderate parameters of crop yield, crop quality, and ET_c should be optimized (Ghaemi and Rafiee, 2016), which can be achieved using good irrigation management.

Previous studies have focused on accurate estimation of water consumption of the crops and vegetables (Liu et al., 2019; Wang et al., 2019), and modeling crop yield and quality partly due to the necessity of sustainable agriculture under environmental degradation along with population growth (Sepaskhah et al., 2011; Ramirez-Perez et al., 2018). Such models can help to assess the most appropriate planning in agro-environmental systems, through optimization of water and fertilizer application. However, more studies are still needed for determining the best irrigation strategies to improve plant growth and yield, especially in manageable environments such as greenhouses.

The feasibility of increasing WUE depends on the biophysical responses of the crops and on economic factors. The objective of producers is very often centered on increasing profits rather than productivity. If water is the limiting factor, increasing WUE is desirable. Where water is not limiting, increasing WUE for maximizing yield may be the most profitable option (Mukherjee et al., 2012). Determining the level of irrigation required to optimize profits, is complex and depends on different factors of plant cultivation (English et al., 2002). To optimize WUE, different parameters of crop yield, ET_c, plant parameters and fruit parameters should be optimized with irrigation management such as irrigation interval and water salinity. Water deficit and salinity have an adverse effect on the potential energy of water, bounding it to the soil matrix by capillary and absorptive forces. This may result in scanty plant growth, the reduction of water uptake and therewith significant yield limitations (Hancioglu et al., 2019). Water salinity decreases transpiration (Al Muaini et al., 2019), which subsequently results in reduced ET_c, and thus it increases WUE, but it may increase soil salinity (EC_e) and decrease crop growth and productivity due to reduction in crop water adsorption. Linear decreases in ET_c have been observed for different plants under different irrigation regimes or water salinity (Shani et al., 2007; Ben-Gal et al., 2008). Despite considerable researches to determine the effects of irrigation regimes or water salinity on ET_c and crop yield (or WUE) (Lekakis and Antonopoulos, 2015; Al Yamani et al., 2017; Assouline, 2019; Hancioglu et al., 2019; Wang et al., 2019), few studies have spotted the combination of optimized amounts of water salinity and irrigation interval in different cultivation environments. WUE optimization is complex regarding various plant and environmental parameters along with various dominancy of each parameter. Integrating multivariate regression modeling (MRM) and structural equation modeling (SEM) can achieve this goal. SEM is a priori approach with the capacity to identify causal relationships between variables by fitting data to the models representing causal hypotheses.

To obtain the best process for controlling effective parameters in crops and vegetables cultivation, different optimization methods have been reported in the literature such as neural network and fuzzy approaches (Gholipoor and Nadali, 2019; Pourmohammadali et al., 2019), response surface methodologies (Lekakis and Antonopoulos, 2015; Wang et al., 2019), population-based algorithms like genetic algorithm (GA), particle swarm optimization and ant colony (Wang et al., 2013; Nguyen et al., 2017; Gavili et al., 2018), or develop a hybrid technique by integrating these methods (Pourmohammadali et al., 2019; Mahmoodi-Eshkaftaki and Rafeie, 2020). However, in recent years a new population-based algorithm named water cycle algorithm (WCA) was suggested by Eskandar et al. (2012) according to the water cycle and how rivers and streams flow downhill towards the sea in the real world. It is very interesting to evaluate the efficiency of this algorithm in optimizing irrigation management. Therefore, the aims of the present study are to (i) use SEM to determine direct and indirect effects of irrigation interval, water salinity and cultivation environment on different parameters of eggplant cultivation, (ii) develop and improve some multivariate models using two years of experiments to specify the relations among the input, moderate and response factors, and (iii) apply WCA and GA to determine the optimum amounts of the factors, and compare their determined optimal values and ranges.

2. Materials and Methods

2.1. Experiment procedure

A simultaneous measurement of eggplant evapotranspiration was obtained in field and greenhouse at Badjgah (29°36'N, 52°32'E), Shiraz University, Shiraz, Iran. The cultivated area in the field and the unheated plastic greenhouse were 1500 and 120 m^2 area, respectively. Uniformly 15 cm height and four leaves seedlings of eggplant *Anamur RZ* cultivar, were transplanted to the plastic micro-lysimeters placed in the field and greenhouse on 5 May. Based on the average eggplant root length suggested by Mirdad (2011), 60 cm height with 35 cm diameter micro-lysimeters were selected in order to avoid root elongation restrictions. Such micro-lysimeters were placed into the ground in the center of each outdoor block, providing similar aerodynamic conditions throughout the whole farm to arrange an appropriate simulation of actual plant conditions in the micro-lysimeters. Some of the soil chemical and physical characteristics include: soil depth (0–30 cm), field capacity and wilting point (30.5 and 11 weight percent, respectively), bulk density (1.03 g/cm^3), pH (7.72), total nitrogen, potassium and phosphorus (0.2%, 600 and 12.5 mg/kg soil, respectively). The plants were daily irrigated with tap water until their full establishment, following which salinity and irrigation interval treatments were begun.

Experiment treatments examined in the outdoor and greenhouse cultivation environments included four salinity levels of 0.8, 2.5, 5 and 7 ds/m, and three irrigation intervals of daily, each 7 days and 14 days. The micro-lysimeters were daily weighted to determine diurnal ET_c values, using the water balance method as indicated in Eq. 1 (Ghaemi and Rafiee, 2016). This daily based weighing insures very little and negligible errors regarding the plant weight increase as a result of the growth process.

$$ET_c = \frac{\left[\frac{(W_n - W_{n+1})}{\rho_w} + (I - D_p)\right]}{A} \tag{1}$$

where I and D_p are the applied and drainage water (cm^3), W_n and W_{n+1} are pot weights in two consecutive days (g), ρ_w is water bulk density (1 g/cm), and A is the top area of the cylindrical pots (cm^2). The weight of water collected in empty pots under each micro-lysimeters was considered as D_p. The crop yield was determined as the weight of hand-harvested fruits during

August and September. WUE was calculated as the ratio of crop yield and total ET_c. The measured salinity of each saturated sample extract was considered as EC_e for each pot. Statistical information of the input irrigation factors and measured parameters are reported in Table 1.

Table 1. Statistical information of the input factors and measured parameters of eggplant cultivation used in the modeling process.

	Factor	Parameter	Value (Type)	Range	Mean	Std Dev
Independent variables	x_1	Irrigation interval (day)	1, 7, 14 (Discrete)	1–14	7.038	5.024
	x_2	Water salinity (ds/m)	0.8, 2.5, 5, 7 (Discrete)	0.8–7	3.819	2.344
	x_3	Environment	Outdoor: 1 & Greenhouse: 2 (Categoric)			
Moderate variables	ET_c	Evapotranspiration (mm)	Numeric (Continuous)	223.9–807.2	489.75	173.86
	EC_e	Soil salinity (ds/m)	Numeric (Continuous)	1.3–16.9	10.12	4.62
	P_H	Plant height (cm)	Numeric (Continuous)	39.7–89.9	60.28	12.21
	R_L	Root length (cm)	Numeric (Continuous)	33.7	42.55	7.49
	S_D	Stem diameter (mm)	Numeric (Continuous)	9–16	11.46	2.10
	F_D	Fruit diameter (cm)	Numeric (Continuous)	2.5–7	4.60	1.23
	F_L	Fruit length (cm)	Numeric (Continuous)	13.5–26.8	19.85	3.42
	N_F	Num. of fruit	Numeric (Continuous)	6–15	9.50	2.12
	Yield	Crop yield (g/plant)	Numeric (Continuous)	560.3–3271.4	1497.11	653.25
Dependent variable	WUE	Water use efficiency (g/(plant-mm))	Numeric (Continuous)	1.8–6.6	3.20	1.09

2.2. Statistical analysis

Three input factors (independent variables), nine moderate variables and a response (dependent variable) were acquired for each experiment treatment. The effect of independent variables on the moderate variables and their effects on the response were statistically determined with one-way ANOVA using SPSS (Ver. 22). The SEM was developed to evaluate the hypothetical responses of ET_c, EC_e, plant parameters, fruit parameters and crop yield to the input factors, and determine the response of WUE to the input and moderate factors. The obtained correlation matrix used for model fitting was implied in AMOS (Ver. 24) software to construct the SEM using a generalized least squares estimation method. Non-significant chi-square test (P> 0.05), high goodness of fit index (GFI> 0.65) and low root mean square errors of approximation (RMSEA< 0.067) indicated the goodness of fit of the SEM in this study. The standardized total effects of all the variables were also calculated among the variables during the analysis.

2.3. Optimization strategy

To determine the best combination of water salinity and irrigation interval for the two cultivation environments (greenhouse and outdoor), the experiments were carried out according to a completely randomized design with three replicates per treatment. WUE as the major response was controlled by measuring different moderate parameters of eggplant cultivation including ET_c, EC_e, plant parameters (plant height, root length, stem diameter), fruit parameters (fruit diameter, fruit length, Num. of fruit) and crop yield. These parameters were modeled using the dataset of the first year of experiments and improved using the dataset of the second year of experiments. The models were used step by step to calculate WUE, and the WUE model was used as the objective function or fitness function in the WCA and GA.

2.3.1. Water cycle algorithm (WCA)

WCA, a nature-inspired metaheuristic optimization method, has been employed to optimize the fitness function of WUE ($J(Z)$). The central ideas underlying WCA are enthused by nature and are developed on characteristics of the water cycle and downhill course of rivers and streams headed for the sea in the real world. Similar to the other metaheuristic approaches for population-based optimization, WCA initiates with an initial population of raindrops. After raining, the random generation of an initial population of design variables (population of streams) takes place. The best stream, stream with the minimum fitness function, is chosen as the sea (Eskandar et al., 2012). Thereafter, a certain number of good streams (the values of the fitness function near to the existing best) are chosen as rivers and the remaining streams flow towards the selected rivers and the sea. Details of the WCA are available in the literature

(Eskandar et al., 2012; Yadav and Verma, 2020). Step-by-step codes for the WCA is comprehensively demonstrated as bellow:

1. Set the input WCA parameters as:

- N_{var} (number of design/decision variables= 3)
- N_{sr} ((number of rivers + sea)= 4 & 8)
- N_{pop} (population size= 100 & 200)
- d_{max} (evaporation condition constant= 10^{-10} & 10^{-16})
- $Max\_Iteration$ (maximum number of iterations= 100 & 500)

2. Create random initial population and form the initial streams (raindrops), rivers, and sea as:

$$\text{Population of raindrops} = \begin{bmatrix} Raindrop_1 \\ Raindrop_2 \\ . \\ . \\ Raindrop_{N_{pop}} \end{bmatrix} = \begin{bmatrix} z_1^1 & z_2^1 & \dots & z_{N_{var}}^1 \\ z_1^2 & z_2^2 & \dots & z_{N_{var}}^2 \\ \vdots & \vdots & \ddots & \vdots \\ z_1^{N_{pop}} & z_2^{N_{pop}} & \dots & z_{N_{var}}^{N_{pop}} \end{bmatrix} \quad (2)$$

N_{sr}= Number of rivers +1(sea)

$N_{Raindrops} = N_{pop} - N_{sr}$

3. Evaluate the value (or cost) of each raindrop with Eq. 3.

$$C_i = \mathrm{Cos}\,t_i = J(Z_1^i, Z_1^i, \dots Z_{N_{var}}^i), i = 1, 2, \dots N_{pop} \quad (3)$$

4. Compute the intensity of flow for rivers and sea via Eq. 4.

$$NS_n = round\left(\left|\frac{\mathrm{Cos}\,t_n}{\sum_{i=1}^{N_{sr}} \mathrm{Cos}\,t_i}\right| \times N_{Raindrops}\right), n = 1, 2, \dots N_{sr} \quad (4)$$

where NS_n denotes the number of streams flowing towards the specific rivers or sea.

5. Calculate the flow of streams to the rivers with Eq. 5, and determine the flow of rivers to the sea (situated at the utmost downhill location) with Eq. 6.

$$Z_{Strean}^{i+1} = Z_{Stream}^i + rand \times C \times (Z_{River}^i - Z_{Stream}^i) \quad (5)$$

$$Z_{River}^{i+1} = Z_{River}^i + rand \times C \times (Z_{Sea}^i - Z_{River}^i) \quad (6)$$

where $rand$ is a uniformly distributed random number between 0 and 1, and C= 2.

6. Interchange the position of river with a stream yielding the best solution. Similarly, interchange the position of river with the sea in case a river finds better solution than the sea.

7. Check the evaporation condition using Eq. 7.

$$d_{\max}^{i+1} = d_{\max}^{i} - \frac{d_{\max}^{i}}{M\,\mathrm{ax}\_\,Iteration} \tag{7}$$

8. Start the raining process (if the evaporation condition is met) using Eq. 8.

$$Z_{Stream}^{new} = LB + rand \times (UB - LB) \tag{8}$$

For the streams which directly flow to the sea,

$$Z_{Stream}^{new} = Z_{Sea} + \sqrt{\mu} \times randn(1, N_{\mathrm{var}}) \tag{9}$$

where LB and UB signify the respective lower and upper bounds well-defined by the given problem. μ (set to 0.1) is a coefficient indicating the range of exploration region near the sea. '$randn$' indicates a normally distributed random number.

9. Reduce the value of the predefined parameter d_{max} using Eq. 7.

10. Check the stopping criterion (convergence criteria). If it is fulfilled, end the algorithm. If not, go back to step 5.

In the present investigation, the performance of WCA was investigated by solving the formulated optimization problem to produce a low mean squared error (MSE). The optimization of the WUE model has been accomplished by means of 32 independent runs with changing the input WCA parameters.

2.3.2. Genetic algorithm (GA)

In GA, a candidate solution to a specific problem is called an individual or a chromosome and consists of a linear list of genes. Each individual represents a point in the search space, and hence a possible solution to the problem. A population consists of a finite number of individuals. Each individual is decided by an evaluation mechanism to obtain his fitness value.

Based on this fitness value and undergoing genetic operators, a new population is generated iteratively with each successive population referred to as a generation. The GA performed the following operations (Mahmoodi-Eshkaftaki et al., 2013):

1. Set the input GA parameters as:
    - Decision variables= 3
    - Population size= 100 & 200
    - Crossover= 0.92 & 0.97
    - Generation= 50 & 150
    - Mutation= 0.4 & 0.75
2. Initialization of random preliminary population;
3. In-loop computation of the fitness function (WUE) of each individual;
4. Perform mutation and crossing-over of individuals;
5. Selection of individuals;
6. Comparison with the minimal desired fitness;
7. Return to step 3 if the stopping criterion is not satisfied.

Optimization of the WUE model has been performed using 32 runs with changing the input GA parameters. The best conditions of eggplant cultivation determined using GA and WCA were compared.

3. Results and Discussion

Measured values of some chief parameters including crop yield, ET_c, EC_e and WUE for each outdoor and greenhouse treatment are given in Table 2. As expected, the highest yields were obtained in control treatments with no stress ($x_1 = 1$ day and $x_2 = 0.8$ ds/m) in both environments and both years of cultivation. Maximum WUE values were found in treatments with x_1 and x_2 levels of 7-days irrigation intervals and 0.8 ds/m for both years and environments. Considering ET_c values of the treatments with $x_1 = 1$ day and $x_2 = 0.8$ ds/m, as those with potential water requirements in each environment, it can be claimed that the highest WUEs were met in treatments with crop water application of about 66% to 74% of potential water requirement (x_1, x_2, x_3 levels of 7,0.8,1 and 7,0.8,2 in outdoor and greenhouse cultivation, respectively). Such results are in complete agreement with those obtained by Senyigit et al. (2011), Serhat (2017) and Darko et al. (2019) which found maximum WUEs calculated for irrigation treatments of 70–75% of potential evapotranspiration.

Table 2. Crop yield, EC_e, ET_c and WUE values obtained from each experiment treatment.

	x_1, x_2, x_3 Levels	Yield (gr/plant)	EC_e (ds/m)	ET_c (mm)	WUE (gr/(plant-mm))	x_1, x_2, x_3 Levels	Yield (gr/plant)	ECe (ds/m)	ETc (mm)	WUE (gr/(plant-mm))
First Year Cultivation	**1,0.8,1**	2278.4	2.7	847	2.7	**1,0.8,2**	3014.4	1.6	599	3.6
	1,2.5,1	1537.4	8.5	681	2.3	**1,2.5,2**	2192.1	9.9	460	3.3
	1,5,1	1496.0	10.6	604	2.5	**1,5,2**	1324.9	11.6	443	2.2
	1,7,1	1340.0	11.4	533	2.5	**1,7,2**	1155.7	13.9	359	2.1
	7,0.8,1	2478.4	3.2	605	4.1	**7,0.8,2**	3512.9	2.1	394	5.8
	7,2.5,1	1524.9	9.8	477	3.2	**7,2.5,2**	2075.8	11.7	294	4.4
	7,5,1	1110.4	12.8	418	2.7	**7,5,2**	1167.1	11.6	276	2.8
	7,7,1	687.3	15.2	380	1.8	**7,7,2**	943.1	14	242	2.5
	14,0.8,1	1739.3	4.3	439	4.0	**14,0.8,2**	3117.3	2.7	233	7.1
	14,2.5,1	977.1	14.4	300	3.3	**14,2.5,2**	1162.6	11.9	171	3.9
	14,5,1	778.2	14.4	251	3.1	**14,5,2**	833.4	12.5	169	3.3
	14,7,1	409.9	17.4	216	1.9	**14,7,2**	501.7	16.4	145	2.3

	x_1, x_2, x_3 Levels	Yield (gr/plant)	ECe (ds/m)	ETc (mm)	WUE (gr/(plant-mm))	x_1, x_2, x_3 Levels	Yield (gr/plant)	ECe (ds/m)	ETc (mm)	WUE (gr/(plant-mm))
Second Year Cultivation	**1,0.8,1**	2384.2	3.1	955	2.5	**1,0.8,2**	2231.9	2	657	3.4
	1,2.5,1	1585.1	7.2	789	2.0	**1,2.5,2**	1639.8	6.8	589	2.8
	1,5,1	1528.6	9.3	675	2.3	**1,5,2**	1220.7	10.6	494	2.5
	1,7,1	1245.3	9.5	553	2.3	**1,7,2**	1018.1	11	431	2.4
	7,0.8,1	1856.2	6.7	707	2.6	**7,0.8,2**	2008.1	3.3	475	4.3
	7,2.5,1	1483.5	9.9	564	2.7	**7,2.5,2**	1285.0	8.4	380	3.4
	7,5,1	1178.3	13.2	479	2.5	**7,5,2**	1158.1	10.3	323	3.6
	7,7,1	843.9	15.7	400	2.1	**7,7,2**	954.6	12.6	301	3.2
	14,0.8,1	1706.3	7.9	483	3.5	**14,0.8,2**	1508.0	5.5	318	4.8
	14,2.5,1	1175.5	14.7	345	3.5	**14,2.5,2**	978.5	9	249	3.9
	14,5,1	778.8	15.2	261	3.0	**14,5,2**	687.6	12.7	217	3.2
	14,7,1	451.4	18.8	205	2.2	**14,7,2**	575.0	16.3	187	3.1

3.1. Synergistic mechanisms of input factors to WUE

The SEM was used to quantify the relative contribution of the input factors and cultivation parameters to the WUE changes (Figure 1). It can be used to estimate the strength of these multiple (direct and indirect) effects, including the standardized direct, indirect and total effects (Figure 1). As shown in the figure, the covariance of independent variables was not significant which is very important for a modeling process. SEM analysis appeared that the independent variables together could explain 92% of ET_c changes, 81% of EC_e changes and 91% of the changes of plant parameters ($Plant\_par = 0.81S\_D + 0.19R\_L + 0.76P\_H + \overbrace{56}^{e1} + \overbrace{26.8}^{e2} + \overbrace{1.5}^{e3}$). The independent variables, ET_c, EC_e and plant parameters together could represent 93% of the changes of fruit parameters ($Fruit\_par = 0.56N\_F + 0.86F\_D + 0.7F\_H + \overbrace{1.86}^{e4} + \overbrace{0.40}^{e5} + \overbrace{0.41}^{e6}$). Such parameters altogether could explain 96% of crop yield changes. Furthermore, all of the moderate variables could describe 100% of WUE changes. As shown in Figure 1, the irrigation interval and salinity directly affected ET_c, EC_e, plant parameters and fruit parameters significantly. The effect of environment on ET_c, EC_e and fruit parameters was not significant, while its effect on the plant parameters was significant. The effect of ET_c, EC_e and plant parameters on the fruit parameters was not significant. ET_c and EC_e directly and significantly impacted the crop yield, while the plant parameters and fruit parameters were not significant. Similar results were obtained by Ghaemi and Rafiee (2016) who reported significant effects of watering regimes and salinity factors on EC_e values in both greenhouse and outdoor environments. Their analysis indicated significant effects of irrigation interval and salinity level on ET_c and crop yield in both environments. Based on a compound analysis performed, they showed a significant effect of environment on ET_c. However, they found no significant effect of environment on crop yield and EC_e.

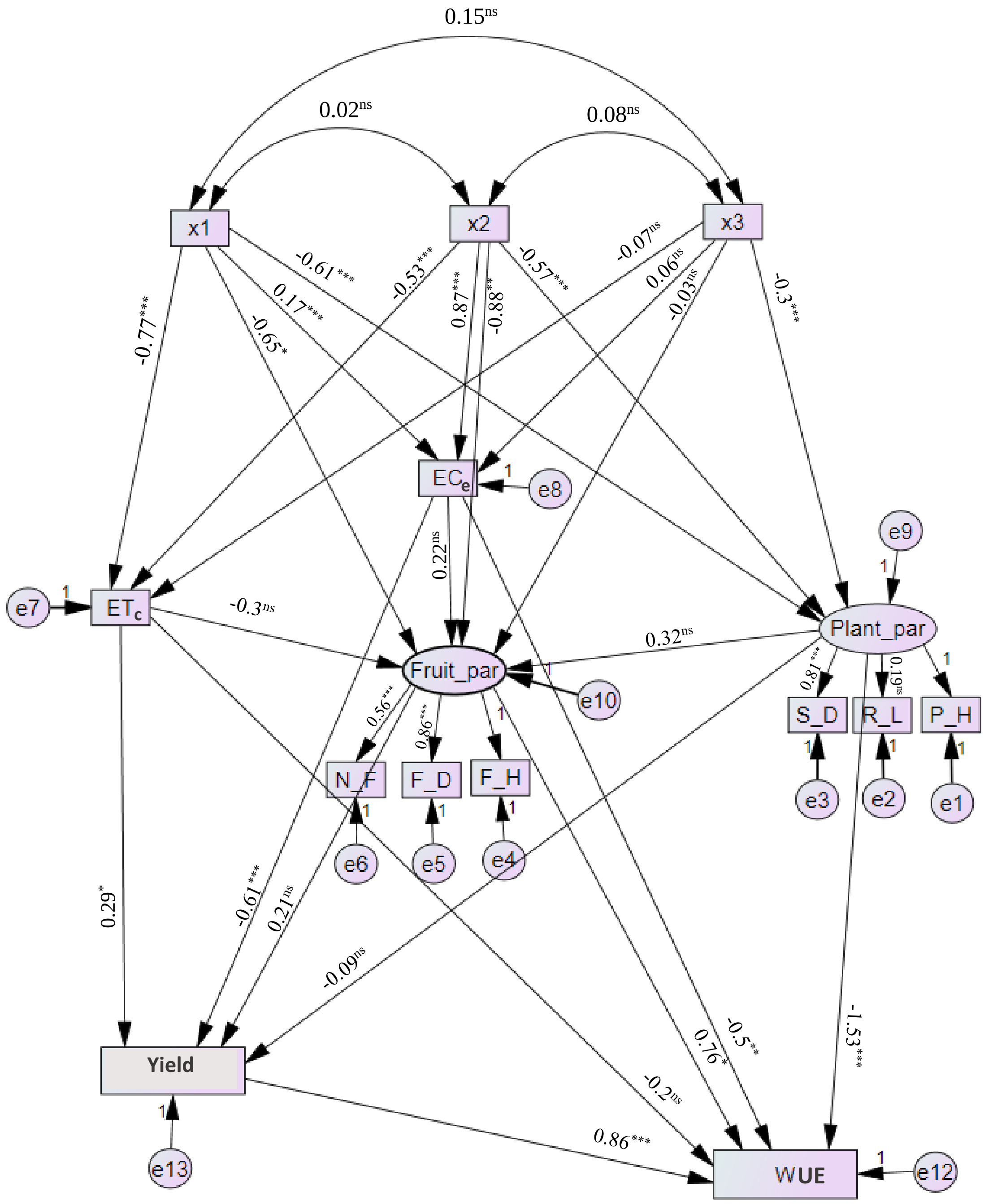

Figure 1. Structural equation model showing the direct and indirect effects of independent variables (x_1: irrigation interval, x_2: salinity, x_3: environment), moderate variables (ET_c, EC_e, plant parameters, fruit parameters, crop yield) and dependent variable (WUE). The numbers adjacent to the arrows are standardized path coefficients, and indicative of the effect size of the relationship. $^{*}P < 0.05$, $^{**}P < 0.01$ and $^{***}P < 0.001$.

It is shown in Figure 1 that EC_e, plant parameters, fruit parameters and crop yield impacted WUE, directly and significantly. However, the effect of ET_c on WUE was not directly significant, it could indirectly impact WUE by significantly affecting crop yield ($\lambda = 0.29$, P

< 0.05 and $\lambda = 0.86$, P< 0.001, respectively). The effect of input factors on WUE was not directly significant, while the input factors indirectly impacted WUE by significantly affecting the moderate variables. As indicated, ET_c, EC_e and plant parameters showed negative effects on WUE, and fruit parameters and crop yield showed positive effects. It was found that all the input factors had negative effects on ET_c, plant parameters and fruit parameters and positive effects on EC_e. This indicates that increasing irrigation intervals and water salinity results in decreases and increases of ET_c and EC_e, respectively. As found in the figure, crop yield and fruit parameters should be increased, and ET_c, EC_e and plant parameters should be decreased in order to increase WUE. The results are consistent with the those of Demirel et al. (2014), Serhat (2017) and Darko et al. (2019), indicating the highest yield as well as the largest and the heaviest eggplant fruits in full irrigation strategy.

Mean comparison using one-way ANOVA showed that all the input factors had significant effects on WUE. Whereas SEM analysis indicated no significant direct effects of input factors on WUE. These confirmed that the input factors indirectly and significantly affected WUE. These findings confirmed that optimal values of the input factors can improve eggplant cultivation very well.

3.2. Multivariate regression modeling (MRM)

Each parameter was modeled based on upstream variables which had a significant effect on that parameter. For instance, WUE gave significant effects of crop yield, EC_e, fruit parameters and plant parameters (As illustrated in Figure 1); thus, WUE was modeled according to these parameters. A similar process was performed for other parameters as well. For this purpose, a quadratic regression model was generalized for each parameter as described in previous studies (Mahmoodi-Eshkaftaki and Mahmoudi, 2021), and Eqs. 10–15 were determined for the parameters. A statistical analysis, analysis of variance with a risk factor of 0.05, was performed to evaluate the accuracy of models. Quality of the models was judged with the coefficient of determination (R^2), adjusted R^2 (AR^2), intercepted R^2 (IR^2) and MSE; the statistical significance of which was determined by an F test (high F-value and low p-value). In a proper model, the p-values of the term coefficients are significant (Mahmoodi-Eshkaftaki and Mahmoudi, 2021). The developed models using the dataset of the first year of experiments and their statistical parameters are illustrated in Table 3.

Table 3. Mathematical models to estimate the moderate and dependent variables developed with the dataset of the first year of experiments.

Mathematical model	Eq. No	*P*-value	AR^2	R^2	MSE
$ET_c = 942.21 - 42.08x_1 - 96.64x_2 + 1.06x_1x_2 + 0.66{x_1}^2 + 6.47{x_2}^2$	(10)	<0.0001	0.92	0.93	1626.61
$EC_e = -0.91 + 0.10x_1 + 4.46x_2 + 0.023x_1x_2 + 0.002{x_1}^2 - 0.37{x_2}^2$	(11)	<0.0001	0.84	0.85	3.79
$Plant\_par = 0.17x_1 - 0.77x_2 + (3.45E + 15)x_3 + 0.014x_1x_2 - 0.13x_1x_3 + 0.83x_2x_3 - 0.063{x_1}^2 - 0.37{x_2}^2 - (1.15E + 15){x_3}^2$	(12)	<0.0001	0.55	0.60	50.43
$Fruit\_par = 32.67 + 0.61x_1 + 0.80x_2 - 0.049x_1x_2 - 0.049{x_1}^2 - 0.186{x_2}^2$	(13)	<0.0001	0.70	0.72	4.34
$Yield = 80.38 + 0.17ET_c + 5.38EC_e - 0.005ET_c \times EC_e - 0.00009{ET_c}^2 - 0.19{EC_e}^2$	(14)	<0.0001	0.80	0.81	5901.5
$WUE = 80.03 - 0.012Yield - 0.87Plant\_par + 0.87Fruit\_par - 3.23EC_e + (6.46E - 05)Yield \times Plant\_par + 0.0002Yield \times Fruit\_par - (1.19E - 05)Yield \times EC_e + 0.003Plant\_par \times Fruit\_par + 0.022Plant\_par \times EC_e - 0.005Fruit\_par \times EC_e - (4.55E - 07)Yield^2 + 0.001Plant\_par^2 - 0.023Fruit\_par^2 + 0.01{EC_e}^2$	(15)	<0.0001	0.61	0.69	0.66

As found in Table 3, all the model's *p*-values were significant, their MSE were low, and R^2 and AR^2 were high. As shown, accuracy of the ET_c model was at most, and accuracy of the Plant_par model was the lowest among the models. R^2 and AR^2 values of the WUE model were high (0.69 and 0.61, respectively), and MSE was low (0.66), indicating high accuracy of WUE calculation. In overall, the statistical quantities calculated for the models showed high accuracy for them to be used in the optimization methods.

The model's coefficients of Eq. 10 show that the model linear terms x_1 and x_2 had negative effects on ET_c while the interaction and squared terms had positive effects. The SEM analysis for ET_c in Figure 1 showed that the standardized regression weight (λ) of the irrigation interval ($\lambda = -0.77$) was higher than the salinity level ($\lambda = -0.53$), indicating that the irrigation interval had a higher effect on ET_c than salinity level. The EC_e model's coefficients in Eq. 11 show that the linear terms x_1 and x_2 had positive effects on EC_e which was in agreement with SEM analysis. The SEM analysis showed that water salinity ($\lambda = 0.87$) had a stronger effect on EC_e than irrigation interval ($\lambda = 0.17$). Considering the model's coefficients of Eq. 12 showed that the linear terms including x_3 had higher positive values compared to other linear terms, while the squared terms including x_3 had higher negative values. This indicates that the coefficients of terms in Eq. 12 cannot be used to determine the most effective variables. As shown in Eq. 13, however, the coefficient values of the terms including x_1 and x_2 were close to each other, SEM analysis showed that the salinity level had a higher negative effect on fruit parameters than irrigation interval. This reveals that daily irrigation with low salinity can optimize fruit parameters significantly; which is in agreement with Simsek et al. (2005) reports. High coefficient values of the terms including EC_e in Eq. 14 showed that EC_e had a higher effect on crop yield than ET_c, which was in confirmation with the SEM findings. As shown in Eq. 15, all the moderate variables except ET_c were used in the WUE model, in which the SEM revealed positive effects of crop yield and fruit parameters, and negative effects of EC_e and plant parameters. Both the MRM and SEM analysis indicated that the irrigation interval and salinity level had negative effects on WUE, i.e. WUE would increase with daily irrigation in low salinity, as confirmed by other researchers (Simsek et al., 2005; Rahil and Qanadillo, 2015). Figure 2 illustrates the predicted values of the parameters obtained by the models versus those observed. As shown, the IR^2 values calculated between the predicted and observed values were near to 1 indicating very high accuracy of the models.

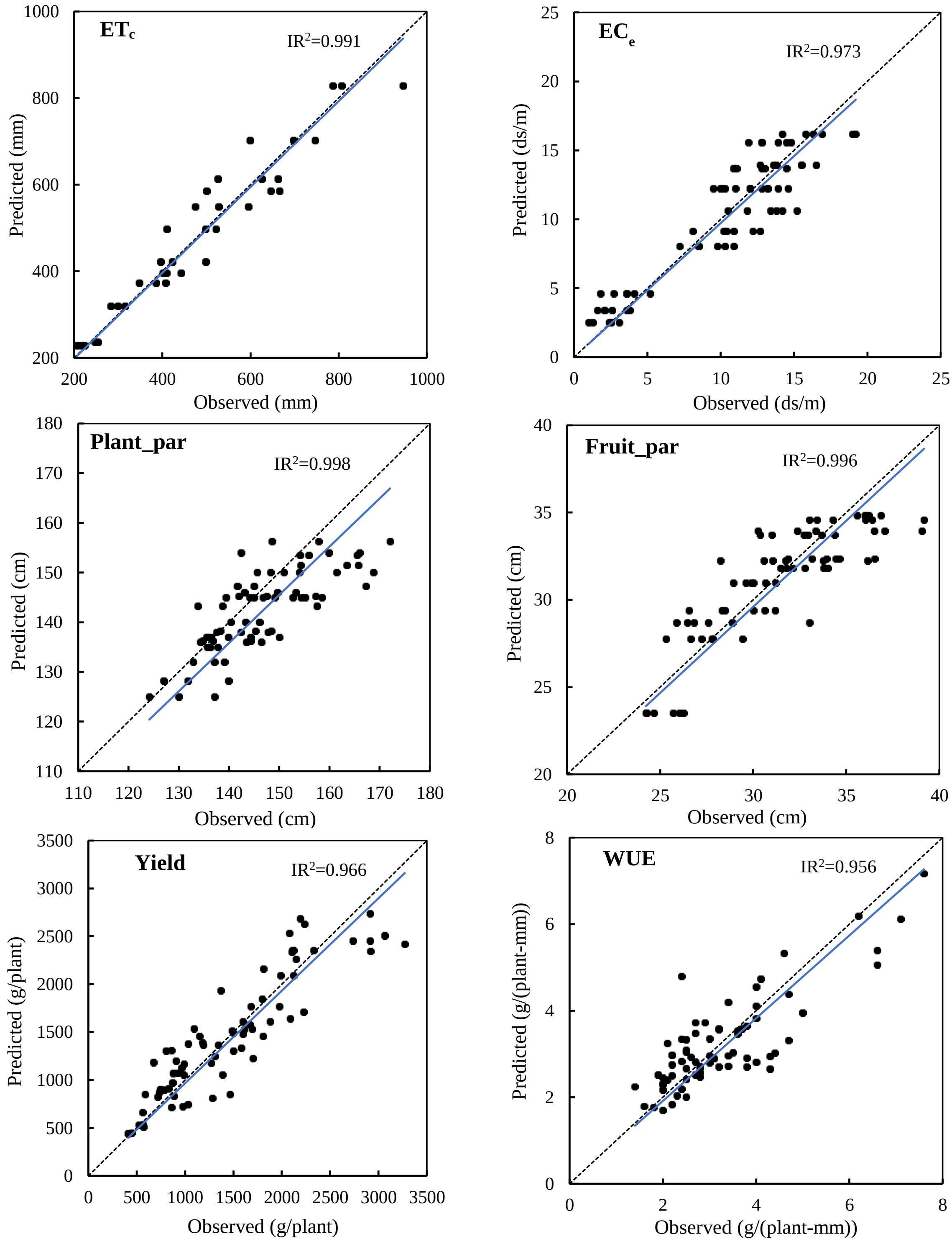

Figure 2. Predicted values versus observed values of different parameters of eggplant cultivation for the first year of experiments using Eqs. 10–15 reported in Table 3.

Analysis showed that some of the terms were not significant and better to be removed from the models. In case of many non-significant model terms, model reduction may improve the model (Mahmoodi-Eshkaftaki and Rafiee, 2020). For this purpose, the models of plant parameters, crop yield and WUE were reduced without significantly decreasing the accuracy of such models. Furthermore, EC_e model was modified by adding some terms according to the dataset of the second year of experiments. The statistical parameters of AR^2, R^2 and MSE of the improved models of EC_e, plant parameters, crop yield and WUE were 0.78, 0.80 and 5.14, 0.58, 0.60 and 46.85, 0.8, 0.81 and 6420.4, and 0.63, 0.69 and 0.5, respectively. These quantities indicate that the improved models are suitable to be used in the optimization process. The structural analysis of the improved models is illustrated in Figure 3.

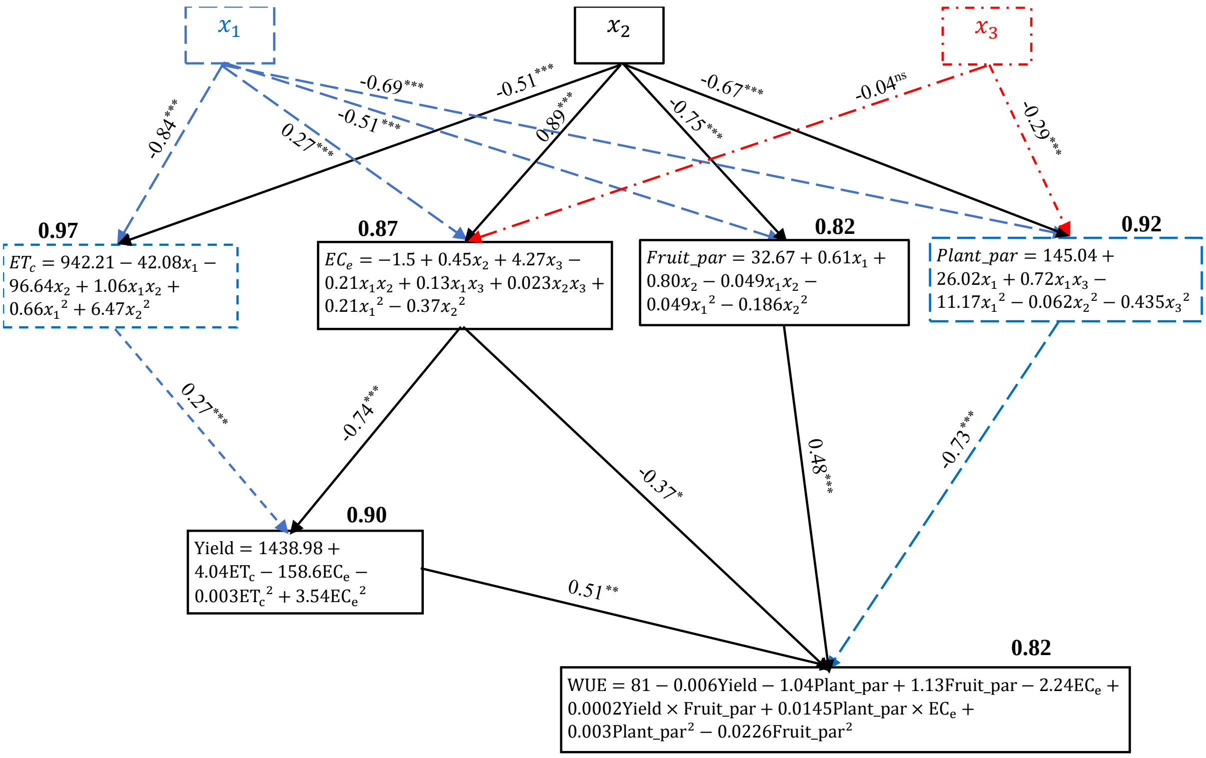

Figure 3. Structural analysis of the improved models to determine the most important factors affecting WUE.

The SEM analysis appeared that x_1 and x_2 together could explain 97% and 82% of the changes of predicted ET_c and fruit parameters, and x_1, x_2 and x_3 together could explain 82% and 92% of the changes of predicted EC_e and plant parameters. ET_c and EC_e together described 90% of the crop yield changes. Further, EC_e, plant parameters, fruit parameters and crop yield together could outline 82% of the predicted WUE changes. All of these quantities were close to 100% indicating that the variables in each model could successfully describe the changes of that model. As shown in the figure, the box including each parameter got a line style from the more effective upstream parameters. As shown, irrigation interval impacted WUE with a more dominant effect on plant parameters, while salinity level impacted the WUE with a more dominant effect on EC_e, crop yield and fruit parameters. These show a low amount of salinity levels will be more important than full irrigation to optimize WUE. Furthermore, the effect of irrigation interval and water salinity on WUE was very high in comparison with the cultivation environment. As shown, Figure 3 was completely successful to illustrate the relationship among the irrigation factors and different parameters of eggplant cultivation.

The improved models in Figure 3, reduced non-significant terms, created from the first year dataset were tested using the dataset of the second year of experiments. Predicted amounts versus observed amounts of the parameters are illustrated in Figure 4. The prediction results of the improved models indicated high accuracy for the models (except for Plant_par model). Therefore, these models can be used in the optimization process successfully.

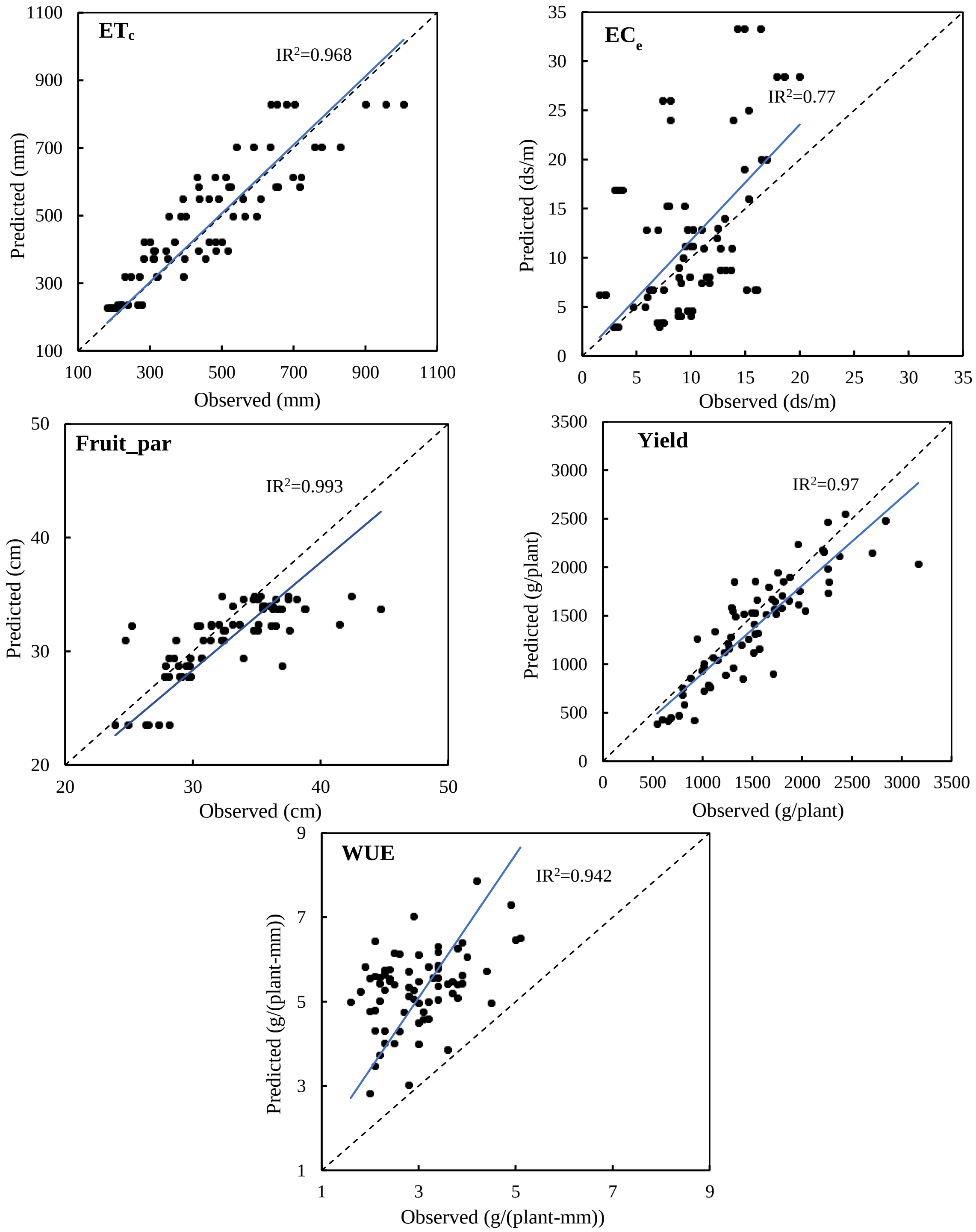

Figure 4. Predicted values versus observed values of different parameters of eggplant cultivation using the improved models tested for the dataset of the second year of experiments.

3.3. Optimization of eggplant cultivation

The optimum amounts of the input factors to improve the performance of eggplant were determined using the optimization methods of WCA and GA. The improved models illustrated in Figure 3 were used step by step to determine WUE. The WUE model was used as the fitness function in the optimization algorithms. The accuracy of Plant_par model was low; therefore, its mean value (146.37 cm) was used to calculate WUE in the optimization process. To determine a suitable structure of WCA in the optimization process, different populations (100, 200), N_{sr} (4, 8), d_{max} (10^{-10}, 10^{-16}) and Max_Iteration (100, 500) were considered. The best ones reaching the highest WUEs were employed to determine optimal amounts of the input factors, moderate parameters and WUE. Values of the fitness function (WUE) during the iteration are illustrated in Figure 5.

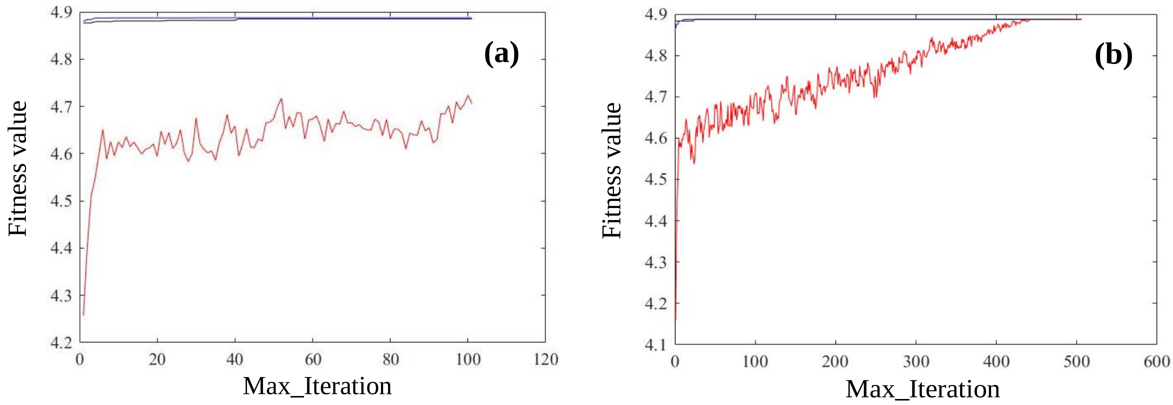

Figure 5. Changes of the fitness function (WUE) for two different Max_Iteration; (a) Max_Iteration=100; (b) Max_Iteration=500.

Setting the WCA parameters, thirty-two runs were done. The four best runs that produced the highest WUEs were reported in Table 4. These runs were used to illustrate the effect of changes in the WCA parameters and input factors on eggplant cultivation. The best run (run 1) revealed the highest WUE, and was selected to report the optimum amounts in this research. It is shown that the optimum amounts for four runs were near to each other, and thus, changing the WCA parameters had no significant effect on the optimal values of cultivation parameters. As described above, the models used in the optimization process were improved according to the dataset of the second year of experiments, also their independent variables were completely similar for both years; therefore, the optimum amounts reported in Table 4 are precise and reliable. To confirm the high accuracy of WCA in the optimization process, results of WCA were compared with GA.

Table 4. Optimal values of the input irrigation factors and parameters of eggplant cultivation with four best WCA.

Factor	Run 1 $\begin{pmatrix} Population: 200 \\ N_{sr}: 4 \\ d_{\max}: 10^{-16} \\ Max\_Iteration: 500 \end{pmatrix}$	Run 2 $\begin{pmatrix} Population: 100 \\ N_{sr}: 8 \\ d_{\max}: 10^{-16} \\ Max\_Iteration: 500 \end{pmatrix}$	Run 3 $\begin{pmatrix} Population: 100 \\ N_{sr}: 4 \\ d_{\max}: 10^{-10} \\ Max\_Iteration: 100 \end{pmatrix}$	Run 4 $\begin{pmatrix} Population: 200 \\ N_{sr}: 8 \\ d_{\max}: 10^{-10} \\ Max\_Iteration: 100 \end{pmatrix}$	Optimum range
Independent variables					
Irrigation interval (day)	**5.15**	4.94	5.057	5.23	(2.13–5.23)
Water salinity (ds/m)	**1.52**	1.53	1.54	1.46	(0.8–2.21)
Environment	**1**	1	1	1	1
Moderate variables					
ET_c (mm)	**526.34**	514.32	521.44	510.30	(346.23–738.19)
EC_e (ds/m)	**7.73**	7.38	7.83	7.52	(4.16–9.45)
Plant parameters (cm)	**146.37**	146.37	146.37	146.37	146.37
Fruit parameters (cm)	**34.94**	34.18	34.94	34.19	(33.81–35.12)
Crop yield (g/plant)	**1913.11**	1912.30	1896.88	1885.13	(1715.7–2190.8)
Response					
WUE (g/(plant-mm))	**4.89**	4.85	4.74	4.68	(3.08–4.89)

To determine a suitable structure of GA for the optimization process, different populations (100, 200), crossover (0.92, 0.97), generation (50, 150) and mutation (0.4, 0.75) were considered. The best ones obtaining the highest WUEs were employed to determine optimal amounts of the input factors, moderate parameters and WUE. The changes of GA parameters during 50 generations to minimize fitness function ($\frac{1}{WUE}$) are illustrated in Figure 6.

As shown in Figure 6a, score $\frac{1}{\mathrm{WUE}}$ decreased to the least value (0.205) up to generation 50, i.e. the WUE amount increased to the most value of 4.887. It was found that with increasing the number of generations, the average distance between the individuals decreased to zero (Figure 6b), the expected number of children decreased to the constant number of one (Figure 6c), and the changes of $\frac{1}{WUE}$ and its mean decreased (Figure 4d). These trends indicate that the GA is well developed and accurately trained. Four best runs of the GA that produced the highest WUEs are reported in Table 5.

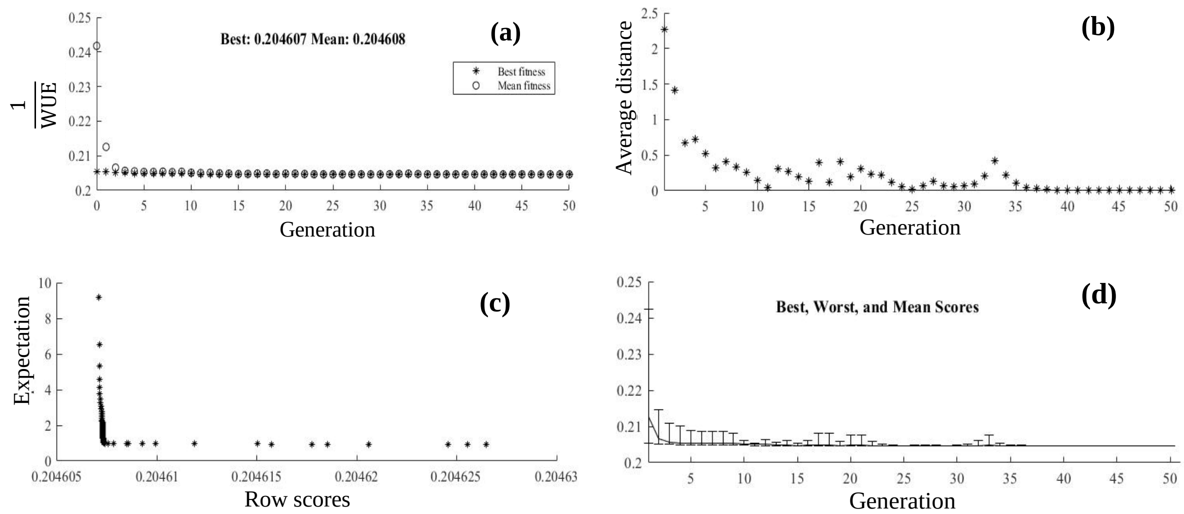

Figure 6. Improve GA parameters during 50 generations to minimize the fitness function ($\frac{1}{WUE}$); (a) Changes of the fitness function versus generation; (b) Average distance between individuals at each generation; (c) Expected number of children versus the raw scores at each generation; (d) Minimum, maximum and mean score values in each generation.

Optimal values obtained for the GA runs were overlayed, and the optimum ranges of the factors were determined illustrated in Table 5. As shown in Tables 4 and 5, the optimum ranges determined using WCA and GA were near to each other, indicating that the optimum ranges are reliable. Furthermore, the models used in the optimization process were improved carefully using the dataset acquired in two years of experiments. Therefore, the optimal values are precise and reliable to be used in the fields.

Table 5. Optimal values of the input irrigation factors and parameters of eggplant cultivation with four best GA.

Factor	Run 3 ($Population: 100$, $Crossover: 0.97$, $Generation: 150$, $Mutation: 0.75$)	Run 2 ($Population: 100$, $Crossover: 0.92$, $Generation: 150$, $Mutation: 0.4$)	Run 1 ($Population: 200$, $Crossover: 0.97$, $Generation: 50$, $Mutation: 0.75$)	Run 4 ($Population: 200$, $Crossover: 0.92$, $Generation: 50$, $Mutation: 0.4$)	Optimum range
Independent variables					
Irrigation interval (day)	4.86	5.39	5.07	5.26	(2.07–6.23)
Water salinity (ds/m)	1.41	1.48	1.68	1.51	(1–2.25)
Environment	1	1	1	1	1
Moderate variables					
ET_c (mm)	537.25	526.36	511.23	516.74	(330.54–764.15)
EC_e (ds/m)	7.30	7.73	7.49	8.20	(4.55–8.59)
Plant parameters (cm)	146.37	146.37	146.37	146.37	146.37
Fruit parameters (cm)	34.93	34.95	34.94	34.95	(34.12–35.70)
Crop yield (g/plant)	1926.18	1878.51	1897.71	1826.89	(1681.7–2260.14)
Response					
WUE (g/(plant-mm))	4.89	4.89	4.63	4.72	(2.95–4.89)

An optimization method has been successfully developed with integrating MRM and desirability analysis to optimize eggplant cultivation in previous studies (Mahmoodi-Eshkaftaki and Rafiee, 2020). They found that the optimum irrigation interval and water salinity for eggplant cultivation were 4.56 days and 1.47 ds/m, respectively, resulting in optimum crop yield (2490.7 g/plant), ET_c (604.76 mm), EC_e (5.27 ds/m) and WUE (3.32 g/(plant-mm)). They used three input factors and four responses, and the responses have been considered in parallel, while all the responses do not have similar effects on eggplant cultivation. For solving this problem, some responses were maximized or minimized, while others were kept within a range, which may increase the optimization error. Therefore in this study, maximizing WUE as the most important parameter of eggplant cultivation was intended. Furthermore, the parameters of ET_c, EC_e, crop yield, plant parameters and fruit parameters moderately affected WUE, which is more similar to reality. Using these assumptions, the best amounts of irrigation interval and water salinity using WCA were determined equal to 5.15 day and 1.52 ds/m cultivated in outdoor. These optimal input factors led to optimized values of ETc, ECe, fruit parameters and crop yield as 526.34 mm, 7.73 ds/m, 34.94 cm and 1913.11

g/plant, respectively, and such optimum amounts of the moderate factors raised WUE values up to 4.89 g/(plant-mm). Optimization of plant cultivation using response surface methodology (RSM) has been reported in other studies (Shani et al., 2007; Kundu et al., 2016). However, the RSM alone cannot determine the optimum amounts accurately enough for such complex systems. Some optimal values of irrigation intervals and water salinity have been reported in the literature for vegetables. Simsek et al. (2005) revealed 100% irrigation water needs to optimize WUE, Ertek et al. (2006) proposed full irrigation with 8-day irrigation intervals as a proper management scenario for vegetables growth, Rahil and Qanadillo (2015) found that a 70% ET_c water level surpassed all other treatments in yield and WUE, and Wan et al. (2010) found saline water up to 4.9 ds/m can be used for irrigation of vegetables in the field. These reports are close to the findings in this study and confirm the results of this study.

The RSM is useful for studying the optimum conditions of a single parameter only (Wang et al., 2019), while in desirable product development, several parameters may have to be optimized simultaneously; especially when a major response influence of some moderate parameters. In a simple system, the effect of factors on a response can be elucidated by modeling the response according to the factors. For a complex system, a response effect of multiple moderate factors and the moderate factors effect of multiple input factors, the relationship among the factors and response can be elucidated using hybrid modeling techniques, like integrated MRM and SEM approaches. Furthermore in the complex system, the population-based optimization algorithms, WCA and GA, would be a helpful tool for the operators with high accuracy.

4. Conclusion

In this study, the relationships among the input irrigation factors and the parameters of eggplant crop were carefully investigated using integrated MRM and SEM. For this purpose, all the variables in the system were divided as independent variables or input factors (irrigation interval, salinity level, environment), moderate variables (ET_c, EC_e, plant parameters, fruit parameters, crop yield) and a dependent variable (WUE). SEM analysis appeared that (i) irrigation interval and salinity significantly impacted ET_c, EC_e, plant parameters and fruit parameters, directly, (ii) ET_c and EC_e directly and significantly impacted the crop yield, while the plant parameters and fruit parameters were not significant, (iii) EC_e, plant parameters, fruit parameters and crop yield directly and significantly impacted WUE, and (iv) effect of input factors on WUE was not directly significant, while they indirectly impacted WUE by significantly affecting the moderate variables. To optimize eggplant cultivation, the relations among the system's factors were modeled using MRM and improved according to two years of experiments. The models were used in the optimization methods, WCA and GA, to optimize irrigation management. The optimal values determined with both optimization methods were close to each other. WCA indicated that the optimum amounts of irrigation interval and water salinity were 5.15 day and 1.52 ds/m cultivated in the outdoor environment. These optimal input factors resulted in optimized ETc, ECe, fruit parameters and crop yield as 526.34 mm, 7.73 ds/m, 34.94 cm and 1913.11 g/plant, respectively, causing to increase WUE up to 4.89 g/(plant-mm). The effect of water intervals, water salinity and environment on different parameters of plant cultivation were studied in this research using a hybrid method, however more effective parameters or methods may be studied in future researches.

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