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Optimum Cropping Pattern Based on Irrigation Water Productivity Using AquaCrop Simulation Model

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ABSTRACT

Optimum cropping pattern increases productivity where input resources are limited. An optimized cropping pattern was developed for a region in Moghan Plain, located in the northwestern Iran, to help water supplier in pre-season decision making on water and land allocation. AquaCrop simulation model was calibrated and executed for yield predictions for 11 different crops and 13 diverse soil types. Evaluation of AquaCrop model showed great robustness for a broad range of crops, even for the crops like canola and alfalfa that were undefined for the model. The precise generated crop water functions revealed the ideal conditions for water allocation by considering the impact of the existing limitation in monthly water availability on optimum cropping pattern without imposing any manipulation. Optimum cropping pattern based on water productivity (OCPWP) was identified by LINGO software. Integrating AquaCrop model and LINGO optimization problem solver created a Decision Support System (DSS) for technical analysis at the regional level. The created DSS is able to support the OCPWP in terms of the complex regional crop-mixture acreage. The ecological considerations introduced diverse winter crops to benefit from autumn precipitations. This strategy decreases irrigation requirement and saves some water for spring/summer high water-demanding crops like alfalfa and cotton, which generally enhances the system resiliency. The generated DSS revealed that 8,762 m^3 water ha^{-1} was required for optimum cropping pattern, which is 8% lower than the maximum and 3% more than the average available water.

Keywords: Crop per drop index, Decision support system, System resiliency.

INTRODUCTION

Water is the most widely existing natural resource on our planet, although about 97.5% of it is saline. However, only a small fraction is available as freshwater (Shiklomanov, 2000). Freshwater is an indispensable natural resource, which plays a vital role in the development of any country. Presently, many countries of the world are experiencing scarcity of fresh water (Mekonnen and Hoekstra, 2016). This finite freshwater resource supports life on the planet, and is threatened by population growth, pollution, and food demands. Therefore, an integrated water management strategy is necessary to avoid the risks of water scarcity (Poff *et al.*, 2016). Failure to develop such a strategy will intimidate health, social and economic well-being, food security, biodiversity and generally promotes human conflicts. As a result, optimal water allocation has become one of the most confusing challenges faced by policy makers. Freshwater scarcity develops

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not only from the physical constraints but also due to inefficient water uses and poor management, which has widened the gap between the water sources and sinks in most parts of the world (Simonovic, 2002). Optimum cropping pattern is a key to close the gap between water supply and water demand.

In many water-scarce countries like Iran, the agricultural sector is the main water consumer that withdraws the main quota of all available freshwater at insufficient water use efficiency (Motiee *et al*., 2001). Some studies have predicted a 14% net increase in the use of water to meet the food demands by the year 2030 compared to 2000 (Rockström *et al*., 2007). Hence, pursuing sustainable technique to increase crop water productivity along with preserving the soil and water resources, is gaining prominence in arid and semiarid regions of the world. Optimum cropping pattern, as a sustainable management technique, could shift the focus on maximizing total production to maximizing water productivity (Debaeke and Aboudrare, 2004; Sepulcre-Cantó *et al*., 2007). Optimum cropping pattern is directly related to the productivity of irrigation systems and greatly contributes to soil and water utilization (Sethi *et al*., 2002). Furthermore, optimal cropping pattern interacts with water requirement and crop yield, as well as optimal profitability. Therefore, cropping pattern plays an important role in rural economic development through its impacts on increased income levels and water use efficiency (Montazar and Rahimikhob, 2008). Analyzing crop responses to water is a multi-variable process, because it depends on soil characteristics, weather conditions, crop growth behaviors, planting dates, farm management, and many other circumstances. Crop simulation models are designed to imitate the behavior of such a complex system (Hoogenboom, 2000). Crop simulation models study the plant response to different combinations of resources and interactions with time phenomena. AquaCrop is a water-driven simulation model that requires a relatively low number of parameters and input data to simulate the yield response to water of major crops cultivated worldwide. The limited AquaCrop inputs are the key elements to investigate and determine the plant response to different resource management while maintaining the sufficient balance between accuracy, simplicity, and robustness (García-Vila *et al*., 2009; Katerji *et al*., 2013; Mkhabela and Bullock, 2012; Rankine *et al*., 2015; Wellens *et al*., 2013). AquaCrop simulates attainable yields of major herbaceous crops as a function of required water under various irrigation conditions in the atmosphere–plant-soil system (Steduto *et al*., 2009). The growth engine of AquaCrop is water-driven, which initially separates ET into soil evaporation and crop transpiration, then translating the crop transpiration into biomass using conservative, crop-specific parameters. The separation avoids the confounding effect of non-productive water requirement (Geerts *et al*., 2010). AquaCrop model generates normalized crop water productivity (Steduto *et al.,* 2007) which is the model’s key approach for applicability in different locations under varying spatio-temporal settings (Steduto and Albrizio, 2005).

Cropping pattern considers regional water and land allocations among different crops. Nonlinear programming models can be used as effective tool to optimize cropping pattern for both ecological and economic goals in the command areas. In crop production system, Water Use Efficiency (WUE) is used to define the crop production per unit volume of water (Ali and Talukder, 2008). WUE refers to the ratio between the final dry matter yield and cumulative crop evapotranspiration. WUE is a useful indicator for quantifying the impact of water management. Water production function is a key output of crop simulation models from which the yield response to water is regularly simulated with empirical functions (Goldhamer and Fereres, 2017).

The objective of the present study was to develop and execute a nonlinear

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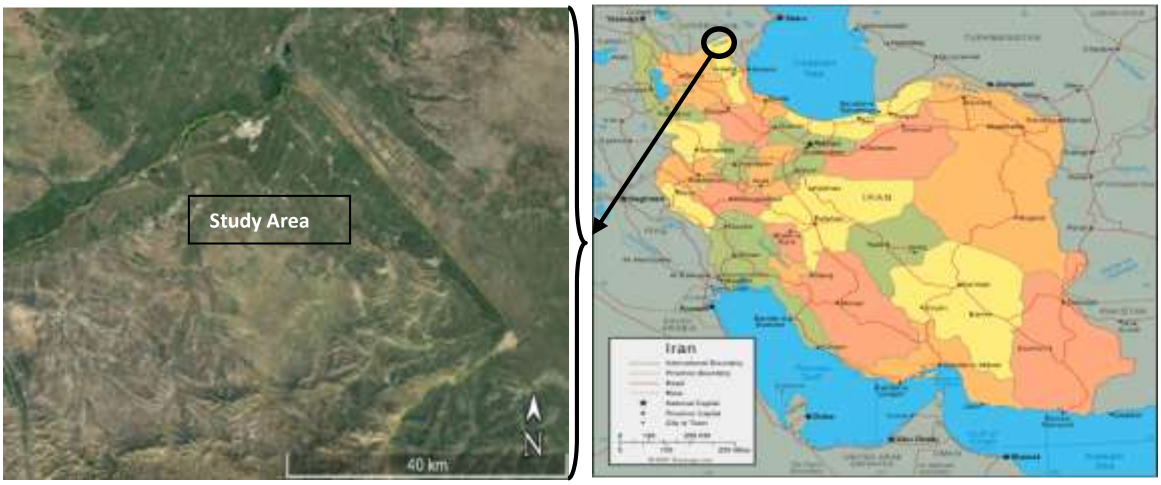

Figure 1. Location of the study area as a part of Moghan Plain in northwest of Iran.

optimization model to determine an optimal cropping pattern based on WUE by Crop Per Drop (CPD) index. CPD index is the total crop yield per one cubic meter of total water used (Monaghan *et al*., 2013). For this purpose, the crop water productivity function is combined with the CPD index as an objective function of the optimization model to design the optimum cropping pattern for part of the Moghan Plain in Iran.

MATERIALS AND METHODS

Description of the Study Area

The study area is a newly developed part of the Moghan Plain located at 47° 33' 18" to 47° 52' 32" E Longitude, 39° 21' 05" to 39° 33' 06" N Latitude, 180 to 330 m above mean sea level, in Ardabil province, northwest of Iran (Figure 1). The Moghan Plain is one of the major agricultural regions in Iran (Nasseri *et al*., 2006). Currently, dryland agriculture is practiced in the main parts of the study area. The area is irrigated through Khodaafarin dam, which is constructed on the Aras River. Due to the land slope and topography, the sprinkler irrigation system is applied. In this study, 11 irrigated crops were chosen according to the regional policy and climatic conditions. The crops included wheat, barley, canola, and sugar beet in winter, cotton, grain maize, soybean and alfalfa in spring and soybean, grain maize and silage maize in summer.

Climate and Soil Data

Moghan Plain has a semi-arid climate with relatively high Evapotranspiration (ET). Previous 20-year climate data were obtained from the nearest weather station (39° 39' N, 47° 55' E, 32 m above mean sea level) in Parsabad City (Figure 2). Based on a recent soil survey, an area of 12,004 ha is covered by 13 different soil types with different characteristics including salinity, hardpan, and slope, (Table 1). The soil survey provides soil classification and physical and chemical properties at different depth intervals of 0.15 m to a depth of 1.5 m (Seyedmohammadi *et al*., 2018). The irrigation water with relatively moderate salinity (1.1 dS m^{-1}) causes soil salinity and imposes a reduction in crop yield.

The runoff Curve Number (CN) of each soil series was calculated based on the soil series physical characteristics to estimate surface runoff from rainfall that occurred during the simulation period. According to the soil series slope, the soils are divided into four groups (A, B, C and D)

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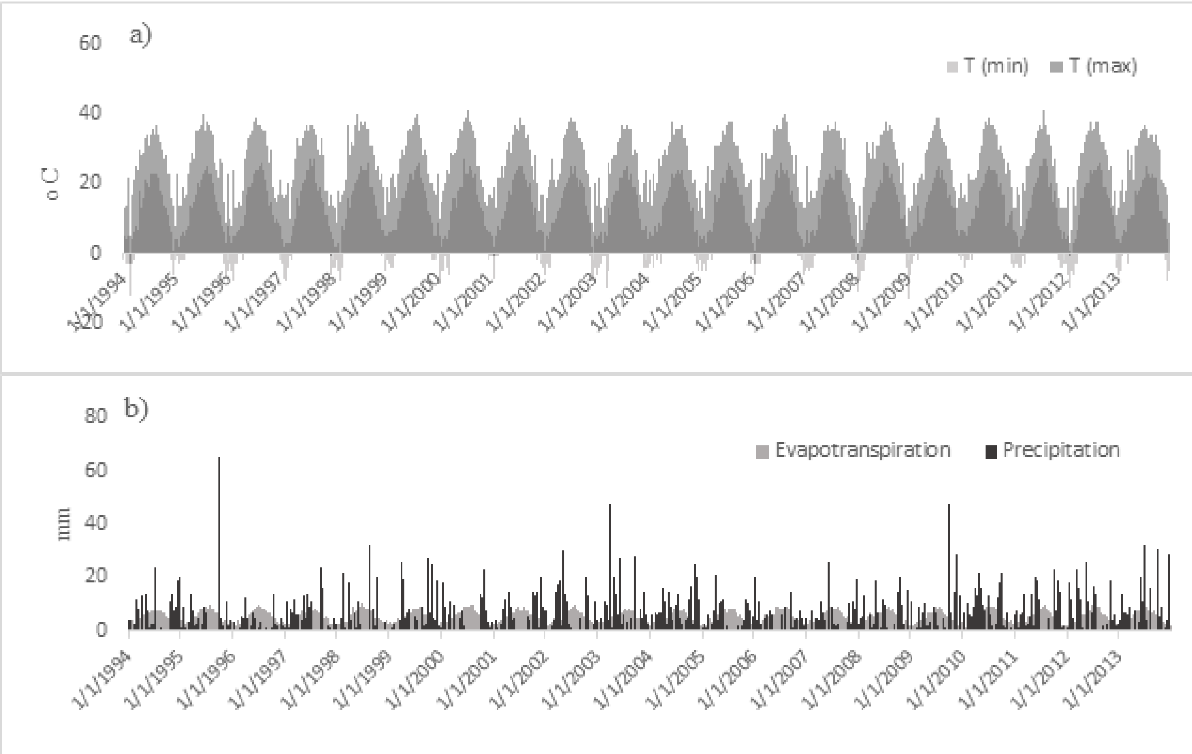

Figure 2. (a) Minimum and maximum temperatures and (b) Evapotranspiration and precipitation in Moghan Plain based on historical data (January 1994 to December 2013).

representing land slopes of 0-2, 2-5, 5-8 and 8-12%, respectively.

Regional Crop Data

Data of crops water consumptions were collected from local experts (Table 4) and crop phenology data were obtained from Oltan Agrometeorological Research Station (39° 36.217' N; 47° 46.733' E, 72 m above mean sea level) located near the study area. -In the present study, according to the local information, the simulations were conducted with sprinkler irrigation, 50% depletion of available moisture and 100% wetted area. Moreover, total irrigation efficiency was assumed to be 65%. All crops have their built-in crop parameters in AquaCrop, except canola, silage maize, and alfalfa. Canola and silage maize are already calibrated (Hsiao *et al*., 2009; Salemi *et al*., 2011; Zeleke *et al*., 2011). A leafy crop using AquaCrop multiple run project was defined to simulate alfalfa for five cutting cycles (Allen *et al*., 1998). The crops' optimum planting dates were previously calibrated for the region (Izadfard *et al*., 2017).

AquaCrop Calibration

AquaCrop version 5.0 (available at http://www.fao.org/aquacrop/en) was used in this study, and all simulations were implemented in the degree-day mode. For the simulations, soil fertility was considered near optimal (about 80%) to cope with the real situation. Runoff was considered by the model based on each soil characteristics. The model calibration was performed by using the observed values from Oltan Agrometeorological Research Station during 2013–2014 cropping seasons. The dry matter yield output of the simulations was

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Table 1. Soil series physical, chemical and hydraulic characteristics in the study area.

	Depth (cm)	Texture	Saturation (%)	EC (dS m^{-1})	pH	OM (%)	FC at 33.3 kPa	WP At 1500 kPa	BD (g cm^{-3})
MA1/ 0-2 % slope	0-20	CL	57.0	1.41	7.81	1.56	29	20	1.41
	20-35	CL	45.0	0.56	7.87	0.52	26	19	1.33
	35-75	SL	29.0	1.07	7.66	0.20	18	12	1.40
	75-120	SCL	52.0	2.90	7.68	0.16	24	17	1.33
	120-170	C	79.0	5.81	7.84	0.00	31	23	1.30
HH3/ 2-5 % slope	0-20	CL	52.0	1.07	7.78	1.22	27	18	1.44
	20-52	C	61.0	8.28	7.72	0.46	32	24	1.31
	52-72	C	61.0	1.34	8.11	0.38	33	25	1.29
	72-91	C	62.0	12.46	7.63	0.19	33	25	1.30
	91-110	C-CL	56.0	10.68	7.68	0.08	30	21	1.36
	110-150	CL	54.0	10.68	7.59	0.00	27	19	1.39
MT1/ 2-5 % slope	0-10	SL	33.0	0.89	7.71	1.07	20	14	1.37
	10-31	LS	38.0	0.53	7.86	0.23	15	10	1.50
	31-41	SL	33.0	0.53	7.84	0.27	19	13	1.38
	41-49	LS	35.0	0.50	7.82	-	15	10	1.50
	58-81	SL	36.0	2.31	7.61	0.30	20	14	1.40
	110-150	SiC	60.0	5.61	7.70	0.68	33	23	1.38
KO4/ 2-5 % slope	0-30	CL	51.0	0.89	7.21	1.00	29	20	1.41
	30-65	C to CL	48.0	2.24	7.54	0.24	30	21	1.37
	65-97	CL	50.0	1.74	7.96	0.04	28	20	1.37
	97-125	SiCL	46.0	8.30	7.60	0.04	30	20	1.44
	125-150	SiCL	45.0	9.13	7.64	0.00	30	19	1.49
GL2/ 2-5 % slope	0-11	CL	49.0	1.91	7.81	1.16	29	19	1.48
	11_30	SiCL	49.0	0.81	7.93	0.60	30	21	1.41
	30-66	SiC	49.0	1.17	7.86	0.28	32	24	1.34
	66-74	SiC	48.0	2.10	7.77	0.15	21	14	1.48
	74-100	SL	44.0	3.99	7.76	0.04	22	13	1.47
	100-150	L	40.0	2.41	7.71	0.04	25	14	1.58
DE1/ 2-5 % slope	0-20	SiC	56.0	0.98	7.57	1.07	32	22	1.39
	20-50	SiC	53.0	0.74	7.93	0.61	32	23	1.37
	50-105	SiC	49.0	2.67	8.29	0.04	32	24	1.35
	105-112	SiC	50.0	3.50	7.86	0.04	29	19	1.51
	112-150	CL	50.0	5.79	7.48	0.00	26	18	1.42
GG2/ 8-12 % slope	0-20	SiCL	58.0	1.17	8.25	0.32	30	18	1.53
	20-42	SiCL	48.0	0.53	7.81	0.64	31	21	1.43
	42-100	SiCL	50.0	0.81	7.70	1.32	31	21	1.43
	100-150	SiCL	52.0	9.96	7.79	0.31	30	21	1.44
SK1/ 2-5 % slope	0-30	SiCL	50.0	0.68	7.68	1.44	31	20	1.49
	30-62	SiC	64.0	2.07	8.12	0.24	33	24	1.35
	62-69	SiC	62.0	3.40	7.89	0.15	29	19	1.51
	69-80	SiCL	59.0	10.80	7.64	0.12	30	20	1.43
	80-115	SiCL	57.0	14.94	7.51	0.01	31	21	1.42
	115-150	SiC to C	57.0	10.79	7.75	0.00	34	25	1.32
KH1/ 2-5 % slope	0-20	CL	51.0	2.67	7.50	1.25	29	20	1.37
	20-40	C	50.0	0.67	7.70	0.61	30	23	1.31
	40-70	CL	47.0	0.98	7.73	0.27	28	20	1.37
	70-76	CL	48.0	1.50	7.70	0.15	27	19	1.42
	76-110	C-CL	54.0	3.38	7.65	0.04	29	21	1.32
	110-150	C-CL	48.0	5.87	7.68	0.11	28	22	1.27
HA2/ 2-5 % and HA3/ 5-8% slope	0-20	SiC-C	61.0	1.66	7.59	1.56	33	24	1.34
	20-47	C	96.0	1.16	8.37	0.92	35	27	1.26
	47-71	C	86.0	10.79	7.83	0.64	36	28	1.25
	71-91	C	74.0	18.26	7.48	0.44	34	26	1.28
	91-150	C	80.0	14.11	7.46	0.32	36	28	1.25
MV3/ 2-5 % and MV4/ 5-8% slope	0-20	C	56.0	2.59	7.66	0.38	33	25	1.29
	20-40	C	58.0	2.41	7.71	0.19	32	25	1.25
	40-70	C to CL	63.0	2.67	7.90	0.15	36	29	1.22
	70-115	C	64.0	4.28	8.00	0.00	36	28	1.23
	115-150	C	71.0	5.34	8.20	0.00	36	28	1.24

OC= Organic Matter; BD= Baulk Density; L= Loam; C= Clay; CL= Clay Loam
FC= Field Capacity; SiC= Silty Clay; SL= Sandy Loam; LS= Loamy Sand; SCL= Sandy Clay Loam
WP= Wilting Point; SiCL= Silty Clay Loam

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converted to actual yield using moisture content values of 15, 14, 75, 11, 12, 14, 15, 80 and 17% for wheat, barley, sugar beet, canola, cotton, soybean, grain maize, silage maize and alfalfa, respectively. The difference between the predictions and observations were minimized by mostly manipulating canopy cover and harvest index using trial and error approach (Steduto *et al*., 2009).

Model Evaluation

Regional crop yield and water requirement were considered in this study for model evaluation. Three statistical indices including coefficient of determination (R^2), Normalized Root Mean Square Error (NRMSE) and d index were employed to compare the simulated results against the observed data. The NRMSE gives a measure of the relative difference of simulated versus observed data. The simulation is considered excellent if NRMSE is less than 10%, good if less than 20%, fair if greater than 20, and poor if greater than 30 (Andarzian *et al*., 2011). The agreement index d represents the agreement between the observed and predicted observations (Willmott, 1981). It overcomes the insensitivity of R^2 or underestimations by the model. It ranges between 0 and 1, with 0 indicating no agreement and 1 indicating a perfect agreement between the predicted and observed data (Legates and McCabe, 1999; Willmott and Matsuura, 2005).

$$\mathrm{NRMSE} = \left[\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n}\right]^{1/2} \times \frac{100}{M} \quad (1)$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (|P'_i| - |O'_i|)^2}\right] \quad (2)$$

CPD DSS Formulation

All 143 functions comprised by 11 crops and 13 soil types were produced by the LINGO software version 11, available at http://www.lindo.com. The yield of each crop can be obtained through crop water production function based on average water requirement for all soil series during the whole growth period. As the generated functions show, crop biomass water use efficiency was determined by the slope of each crop water production function. The water use efficiency developed by AquaCrop model integrates the precipitation and soil water content. The main optimization function (Z) has been comprised by 143 crop/soil functions (11 crops×13 soil types). The average crop water requirement for each crop was introduced to the main optimizing model. The comparable yield of each crop/soil function was calculated using average irrigation water requirement. By introducing the average crop water requirement to the main function, the optimum acreage for each crop was determined. In order to optimize the water use efficiency of each crop/soil unit, the main objective functions were formulated based on all crop/soil units for CPD index and monthly crop water requirement indices. The constraints imposed on the objective function of the model were total available Water (W), monthly available water (m), Total area (TL), each soil series area (sL), first and second crop Production function (P) in a year, optimum acreage of each crop (S) and calculated CPD index (A). Ten percent of the total land was considered under fallow. Maximizing the main function (Z) based on the constraints was computed by LINGO software. While the total land, total water, monthly water, and each crop/soil CPD are constant, individual crop acreage and consequently crop production need to be optimized to determine maximum production of total area. Some studies have shown that crop water function optimization can be more accurately solved by nonlinear structures compared to linear methods (Barati *et al*., 2020; Zhao *et al*., 2017).

$$Max\ Z = \sum_{j=1}^{13} \sum_{i=1}^{11} A_{ij} P_{ij} S_{ij} \quad (3)$$

$$\sum_{j=1}^{13} S_j \leq TL \quad (4)$$

$$\sum_{j=1}^{13} S_j \leq sL \tag{5}$$

$$\sum_{j=1}^{13} \sum_{i=1}^{11} A_{ij} P_{ij} S_{ij} \leq W \tag{6}$$

$$\sum_{j=1}^{13} \sum_{i=1}^{11} A_{ij} P_{ij} S_{ij} \leq m \tag{7}$$

RESULTS AND DISCUSSION

Calculation of ET_o is a critical parameter for model accuracy. In the current study, the available climatic parameters including solar radiation, wind speed, air pressure, temperature and precipitation were used to calculate ET_o in FAO ET calculator (Raes and Munoz, 2009). The annual temperature range is acceptable for most of the crops from January to July. The 271 mm annual precipitation compared to 2,221 mm of ET_o, is not enough for dry farming system, except for wheat and barley.

Fine-Tuned Model

AquaCrop model was fine-tuned for 11 different field crops under full irrigation based on the obtained phenology data. The calibrated parameters are shown in four different factor groups in Table 2. The simulated yields were compared to the corresponding regional crop yields. As illustrated in Table 3, sugar beet showed the best model performance by NRMSE= 10.33, R^2= 0.93 and d Index= 0.88. It could be resulting by adding up the sugar beet-related high moisture content, which reduces the bias of error in dry mass simulation. On the other hand, cotton showed the weakest result, which could be the result of using local cotton variety with different growth habits. The same conclusion has been reported for local cotton varieties (Farahani *et al*., 2009). What is clear from Table 3 is the weakness of R^2 as a single statistical factor for model performance.

It should be noted that the NRMSE and d index tended together and the low NRMSE index was accompanied by higher d index and vice versa. However, considering summer soybean as an exception, NRMSE was the most accurate index.

Results showed the model capability to simulate average yield for most of the cultivated crops in the region. Similar results have proved the capability of AquaCrop model in simulations of different crops' yield in other regions (Todorovic *et al*., 2009). For some of the crops, the irrigation measurements were available. The simulated irrigation was evaluated against the corresponding observations (Figure 3). Based on these results, the model could perfectly simulate the water requirement compared to the measured data.

For water requirement evaluation, the R^2 and NRMSE were 0.91 and 12.57, respectively. The model could simulate water requirement more accurately with respect to yield. This could be explained by the inadequacy of the measured crop water requirements data. Other studies have reported diverse findings depending on the crop, climate, and water stress severity (Horemans *et al*., 2017; Vanuytrecht *et al*., 2014).

The evaluated AquaCrop model was executed to simulate the yield and water requirement under full irrigation scenario by the model generated irrigation schedule for all combinations of crops and soil series. In this study, the cumulative irrigation amount was plotted against the biomass. Then, crop water production function for each crop/soil unit has been calculated based on the plotted values.

According to Figure 4, winter sugar beet and winter wheat showed the lowest R^2 compared to other crops. This could be a result of less water requirements during early weeks after planting these two winter crops (Kang *et al*., 2003; Liu *et al*., 2002; Santos *et al*., 2008). The cotton, soybean, silage maize and alfalfa functions demonstrated ascending trend compared to other crops that followed a descending

Table 2. Selected AquaCrop model fine-tuned parameters for the main cultivated crops in the study area.

Cultivation seasons													
	Spring				Summer			Winter					
Crop parameters	Alfalfa	Cotton	Soybean	Maize[a]	Soybean	Maize[b]	Maize[c]	Wheat	Barley	Canola	Sugar Beat	Units	Methods
Growth factors													
Base temperature	0	12	5	8	5	8	8	0	0	0	5	ºC	D
Cut-off temperature	30	35	30	30	30	30	30	26	15	30	30	ºC	D
Crop water productivity	17	15	15	33.7	15	33.7	33.7	15	15	18	17	g m^{-2}	E
Expansion upper threshold	0.2	0.2	0.15	0.14	0.15	0.14	0.14	0.2	0.2	0.2	0.2	-	D
Expansion lower threshold	0.7	0.7	0.65	0.72	0.65	0.72	0.72	0.65	0.6	0.55	0.6	-	D
Morphologic factors													
Initial canopy cover	1.8	0.72	0.1	0.49	0.1	0.49	0.49	6.75	6	2.2	0.1	%	E
Maximum canopy cover	87	93	77	89	78	89	90	88	92	78	96	%	C
Canopy growth coefficient	21.9	7.8	13.6	12.7	13.6	12.7	12.7	3.9	3.7	8.9	5.1	% Day	C
Canopy decline coefficient	0.8	0.24	0.15	0.56	0.15	0.56	0.56	0.38	0.6	0.4	0.38	% GDD	C
Maximum root depth	150	200	200	230	200	230	230	150	130	100	100	cm	D
Phenology factors													
Time to emergence	-	36	200	96	162	120	120	150	98	191	125	GDD	C
Time to reach full canopy	75	1242	1522	901	998	766	766	1203	1003	1139	852	GDD	C
Time to reach senescence	362	1419	2200	1664	1609	1443	1443	1704	1517	1556	1138	GDD	C
Time to reach harvest	376	1918	2700	2165	2001	1723	1454	2414	1805	1757	1773	GDD	C
Planting and harvest factors													
Sowing date[d]	15 Mar	15 May	30 May	15 Apr	10 Jul	5 Jul	5 Jul	30 Sep	20 Nov	10 Nov	10 Sep	Gregorian Calendar	C
Harvest index	85	35	40	48	40	48	94	48	45	30	71	%	E

[a] Spring, [b] Summer, [c] Silage, [d] Sowing dates have been calibrated (data not shown), C: Calibrate, D: Default, E: Estimate

function (Figure 4). This different trend line for these plants could be justified by the indeterminate growing nature of cotton and soybean and harvesting time of silage maize and alfalfa (Adeboye *et al*., 2015; Marek *et al*., 2017).

CPD Optimum Cropping Pattern

This study adopted the crop yield per unit of consumed water as the main productivity index for optimum cropping pattern. The optimum area for each crop in each soil series has been defined. The optimum

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Table 3. Summary of statistical indices used for model evaluation between simulated crop yields and measured average yield in Moghan Plain (Parsabad).

Crops	Alfalfa	Cotton	Soybean[a]	Maize[a]	Soybean[b]	Maize[b]	Maize	Wheat	Barley	Canola	Sugar beet
No. of Observations	6	4	3	4	4	3	3	11	9	6	3
R^2	0.6	0.8	0.74	0.75	0.79	0.8	0.76	0.71	0.85	0.72	0.93
NRMSE	28.19	35.84	25.18	28.89	14.93	27.84	21	18.78	29.81	10.89	10.33
d Index	0.23	0.35	0.44	0.42	0.98	0.38	0.4	0.68	0.55	0.96	0.88

[a] Spring, [b] Summer, 3: Silage

Table 4. Measured crop water requirement based on local experts' data.

Net irrigation requirement (m^3 ha^{-1})	Winter barley	Winter canola	Winter wheat	Winter sugar beat	Spring maize	Summer maize	Spring soybean	Summer soybean
	2150	2600	2350	5000	6050	4040	5680	2730

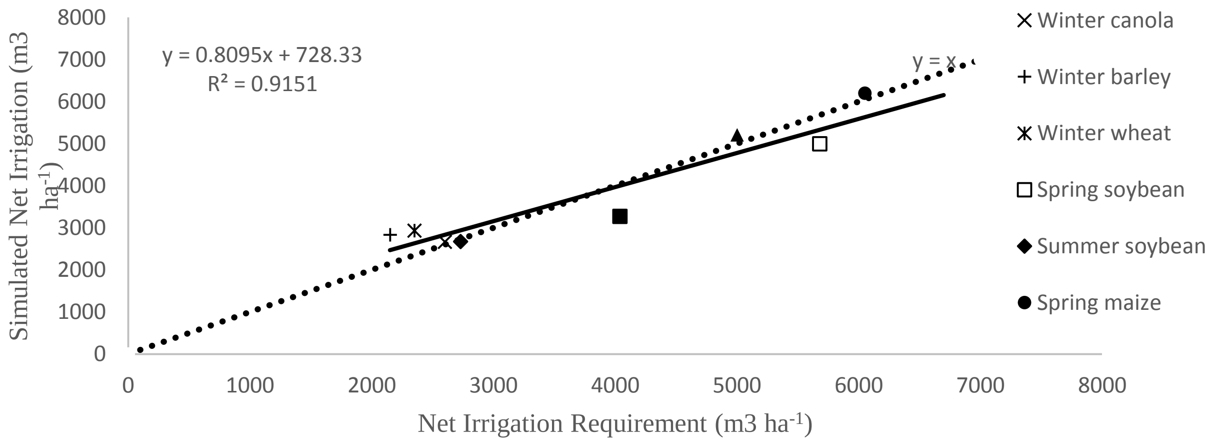

Figure 3. Comparison between simulated crop water requirement and actual measurements.

acreage of each crop is shown in Figure 5. During the cropping pattern optimization, no limitation was imposed on crop acreage. Similar DSS has been generated for other regions (García-Vila and Fereres, 2012; Mysiak *et al*., 2005). Using crop water functions for CPD optimum cropping pattern illustrated the best acreage for each crop in response to water requirement. As shown in Figure 5, the 40% wheat acreage in the current cropping pattern has been allocated to barely, canola and sugar beet in the optimum cropping pattern. However, the canola acreage is too small because the crop production compared to water requirement is not that much. In fact, oil production makes a very low water use efficiency compared to other carbohydrate producing crops (Faraji *et al*., 2009). Increasing crop variation decreases the farmers' economical risk regarding climate and water restrictions. In fact, variation is a key element in sustainability by which resiliency and risk management may be improved (Bullock *et al*., 2017; Mehri *et al*., 2020).

Imposing winter crops to optimum cropping pattern by DSS system increased the total water productivity, because part of the water requirement is supplied by the autumn precipitations. In fact, applying the developed DSS to the study area revealed winter crop variations instead of current vast

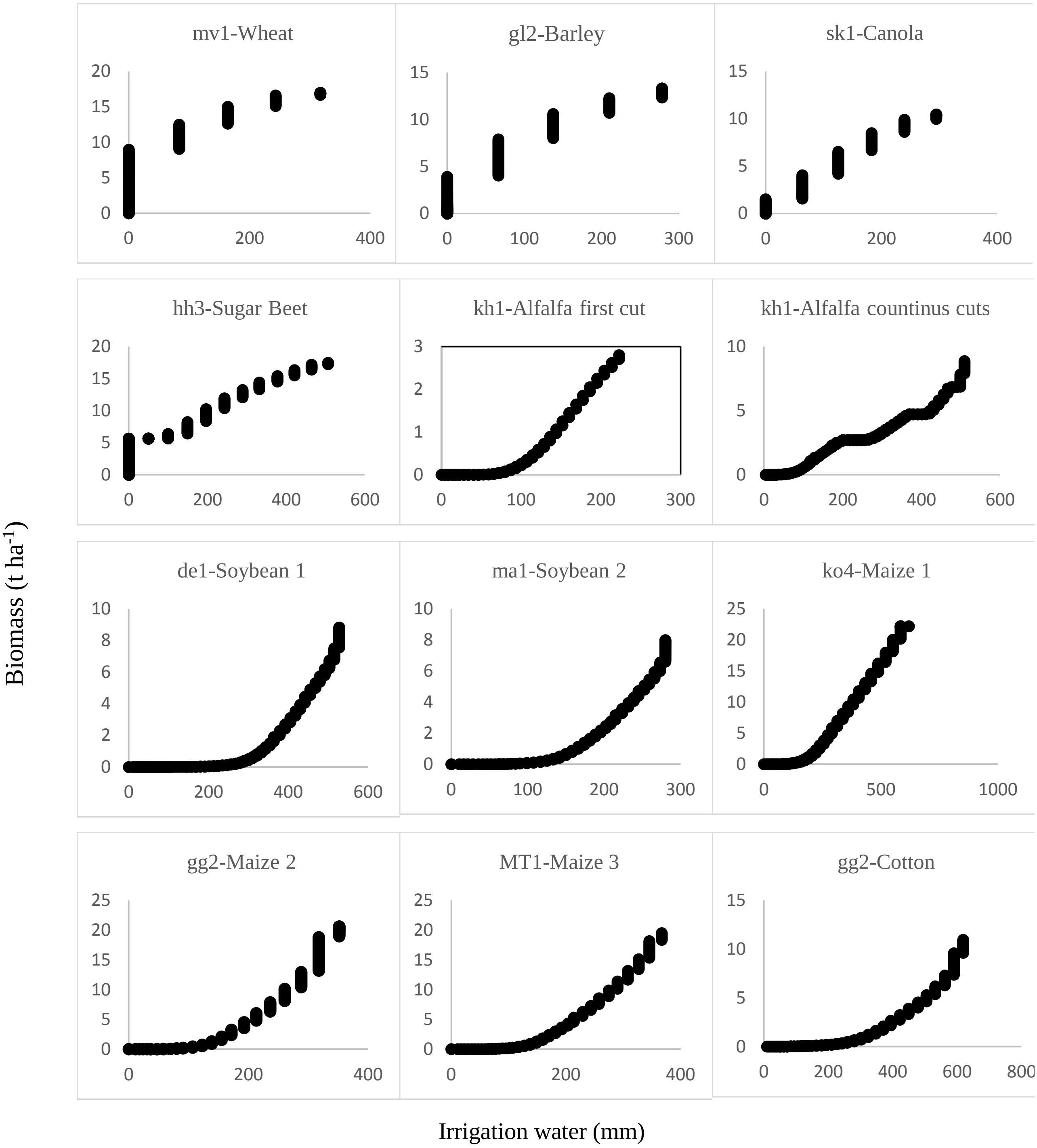

Figure 4. Some of the main crop/soil water functions generated by AquaCrop model for different crops and soils series.

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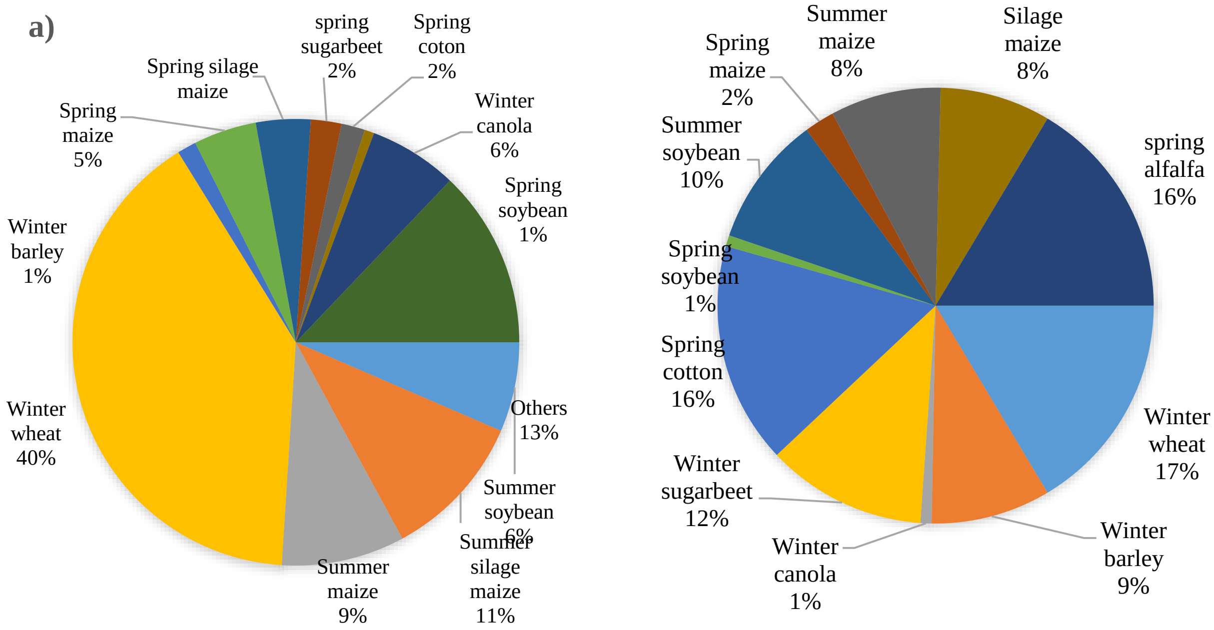

Figure 5. (a) Current Moghan Plain (Parsabad) cropping pattern and (b) CPD index-based cropping pattern for the study area.

winter wheat cultivation. Therefore, the presented winter crops that are harvested before the summer increase water availability for high water demanding crops like alfalfa and cotton during the warm season. Optimum acreage for cotton and alfalfa was 16%, causing low acreage for spring grain maize and soybean (1 and 2%), respectively. Cultivation variation helps to better manage the irrigation schedule regarding different crop irrigation water requirement. This results from the optimized model, giving priority to allocate water to the most water-use efficient crops considering climate, soil, and yield.

Accordingly, it is the duty of developed DSS to balance the regional contradictions among water resources allocation, crop yield, and CPD index (Yang *et al*., 2017).

Monthly Water Requirement

The monthly water requirement was calculated by daily crop water requirement and used as a monthly water coefficient in the optimization process. As Table 5 shows, from May to August was the major water demanding competition, and November was the minor. This is because the study area has high evapotranspiration during this period, especially in July. According to Table 5, total water requirement for optimum cropping pattern was 10.56 Mm^3 and the peak water requirement was in May and July. The increase of water requirement in these two months was the upper threshold to limit the crop acreages. The monthly irrigation water requirement for each crop is shown in Table 6. Water requirement of alfalfa, cotton, sugar beet, and wheat for optimum cropping pattern was 2.65, 2.35, 1.38 and 1.22 Mm^3, respectively.

As shown in Table 5 and Table 6, the total required water in these two tables is a little bit different based on daily and monthly water requirement calculations. The simulated CPD index ranges from 0.36 to 2.46 kg m^{-3} (Table 7), which is confirmed by similar studies (Ahmadzadeh *et al*., 2016). The highest CPD belongs to grain maize due to short growing season and high yield. The

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Table 5. Simulated monthly and total water required for optimum cropping pattern.

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Total
Monthly required water (mm^3)	0.207	0.079	0.716	1.358	2.104	1.984	2.104	1.413	0.483	0.056	0.012	0.044	10.566

Table 6. Simulated crop and total water requirement based on optimum cropping pattern acreages.

Crop water requirement (mm^3)	Wheat	Barley	Canola	Sugar beet	Cotton	Soybean[a]	Soybean[b]	Maize[a]	Maize[b]	Maize[c]	Alfalfa	Total
	1.220	0.649	0.056	1.380	2.349	0.093	0.573	0.311	0.628	0.608	2.645	10.51

[a] Spring, [b] Summer, [c] Silage

Table 7. Simulated crop CPD and total CPD based on optimum cropping pattern acreages.

CPD index (kg m^{-3})	Wheat	Barley	Canola	Sugar beet	Cotton	Soybean[a]	Soybean[b]	Maize[a]	Maize[b]	Maize[c]	Alfalfa	Total
	1.57	1.20	0.67	1.63	0.36	0.41	0.60	1.12	2.40	2.46	1.05	1.22

[a] Spring, [b] Summer, [c] Silage

two lowest CPD indices were 0.36 and 0.67 kg m^{-3} for cotton and canola, respectively. As discussed earlier, the oil production causes low water productivity as well as lint production (Ibragimov *et al*., 2007). Nevertheless, the share of canola and cotton in optimum cropping pattern was not the same. It seems that the water availability during the spring season and winter crop competition are effective in this respect. Total CPD value was 1.23 kg m^{-3} for the whole optimum cropping pattern. Total CPD index for optimum cropping pattern indicated obvious benefit per unit water use.

The global CPD index limits for wheat, cotton, and grain maize are 0.6-1.7, 0.14-0.33 and 1.1-2.7 kg/m^3. Universally measured average crop water production values per unit consumed water are 1.09, 0.23 and 1.80 kg m^{-3} for wheat, cotton, and grain maize, respectively (Zwart and Bastiaanssen, 2004). Considering the global range and average crop water productivity, the simulated CPDs are within the reported limits. The calculated CPD index for cotton (0.36 kg m^{-3}) is higher than the global range, and CPD index for wheat (1.56 kg m^{-3}) and for grain maize (2.46 kg m^{-3}) are near the maximum reported values. Although the recent remotely-sensed studies stated higher CPD values, normalized for the region and climate (Bastiaanssen and Steduto, 2017), the simulated total CPD for optimum cropping pattern considering the climate and soil could be acceptable.

Monthly available water and monthly water requirement appeared as advantages in the developed DSS by saving adequate water for each crop. In fact, without accounting monthly available water, some high yield crops like sugar beet could move out all other crops from the picture. The reasonable simulated yields support the suitability of AquaCrop model. The developed optimum cropping pattern has shown to be a good tool to perform scenario analysis, assisting irrigation scheme managers, water suppliers, and policy makers. Different amounts of available water were defined for the study area. Hence, three scenarios were generated for the ecologically available water (maximum 9,500 m^3 ha^{-1}, average 8,500 m^3 ha^{-1}, and minimum 7,500 m^3 ha^{-1}) for the region. The generated DSS clarified that 8,762 m^3 $ha^{-1}$is the optimum available water for the

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designed cropping pattern. In case of changes in basin conditions, the DSS could manage the new situation by altering the optimum acreage and location of each cultivated crop.

CONCLUSIONS

Combining a crop simulation model with an optimization program is a complex task. Here, the AquaCrop simulation model was used to generate nonlinear crop water production functions for different crops and soil types. This paper proposed a method for agricultural water resources management. The research demonstrated that water use efficiency alone could not be enough for this management; but still, it is a trusted indicator. This study did not consider uncertainties and economic considerations, which are ubiquitous in water resources management. The developed system could be applied to a real-world study in part of the Moghan Plain. Decision makers for water resources management can choose water allocation scheme according to the optimum scenarios and actual economic considerations. Although economic situations are altering every year, but ecological conditions are more stable. The impact of socio-economic factors on optimum cropping pattern deserves further studies.

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الگوی کشت بهینه بر اساس کارایی آب آبیاری با استفاده از مدل آکوآ کراپ

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چکیده

الگوی کشت بهینه در صورت محدود بودن منابع ورودی، بهره‌وری را افزایش می‌دهد. یک الگوی کشت بهینه برای کمک به تأمین آب در تصمیم گیری‌های پیش از فصل در خصوص تخصیص آب و زمین برای منطقه‌ای در دشت مغان، واقع در شمال غربی ایران ساخته شد. مدل شبیه سازی AquaCrop برای 11 محصول متفاوت و 13 نوع خاک مخالف کالیبره و برای پیش بینی عملکرد استفاده شد. مدل صحت سنجی شده AquaCrop برای شبیه سازی طیف گسترده محصولات زراعی، حتی برای محصولاتی مانند کلزا و یونجه که در آن تعریف نشده بود، توانایی بالایی را نشان داد. توابع آب زراعی دقیق با توجه به محدودیت های آب ماهانه موجود بدون دستورزی و تحمیل در الگوی بهینه، شرایط ایده آل در تخصیص آب را مشخص کرد. الگوی کشت بهینه مبتنی بر بهره‌وری آب با استفاده از نرم افزار LINGO مشخص شد. تلفیق مدل AquaCrop و مدل LINGO ، یک سیستم پشتیبانی تصمیم (DSS) برای تجزیه و تحلیل فنی در سطح منطقه ایجاد کرد. سیستم پشتیبانی از تصمیم قادر به پشتیبانی از الگوی کشت بهینه از نظر پیچیدگی میزان سطح محصولات محتلف زراعی است. بهره مندی از ملاحظات اکولوژیکی موجب معرفی طیف متنوعی از محصولات پاییزه در الگوی کشت بهینه شد. این راهبرد نیاز آبیاری را کاهش داده و مقداری آب برای محصولات بهاره/ تابستانه با نیاز آبی زیاد مانند یونجه و پنبه را آزاد نمود که به طور کلی باعث تقویت مقاومت سیستم زراعی می‌شود. بر اساس نظام پشتیبانی از تصمیم توسعه داده شده، 8762 متر مکعب در هکتار آب برای الگوی کشت بهینه نیاز است که 8٪ پایین تر از حداکثر آب در دسترس و 3٪ بیشتر از حد متوسط است.

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