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RESEARCH PAPER

An Integrated Framework for Optimal Irrigation Planning Under Uncertainty: Application of Soil, Water, Atmosphere and Plant Modeling

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Abstract
In this paper, an innovative framework is developed for simulating the water distribution in agricultural lands considering existing constraints related to soil, water, atmosphere and plant. Some nonlinear operating rules are formulated for the irrigation planning and groundwater management in Shahrekord plain in Iran. Evapotranspiration values are estimated based on a real-time modeling. Groundwater exploitations are limited for each irrigated area by considering its actual water requirement and soil moisture balance with daily time steps at the root zone. Moreover, this work introduces an approach for taking into account the uncertainty of available water. For this purpose, the membership functions of fuzzy inputs are discretized into five levels and then a multiobjective optimization model is developed to find the extreme values of economic efficiency of irrigation water for different levels. The results show that under limited water conditions, the economic productivity could be further improved when water, soil, atmosphere and crop relationships are simultaneously considered. In the proposed cropping pattern, the net annual return was increased by more than 43% comparing to the existing cropping pattern. Furthermore, different efficiency criteria for crops with higher values of yield production (e.g., potato, maize, sugar beet and alfalfa) are more affected by the existing uncertainties.

Keywords Uncertainty analysis · Cropping pattern · Water use efficiency · Fuzzy set theory · Shahrekord plain

1 Introduction

Most research in the face of the groundwater scarcity and agricultural development has focused on efficient strategies of water allocation to increase the existing water use efficiency (Turner et al. 2004; Lalehzari and Boroomand-Nasab 2017). Irrigation planning in agriculture as the main consumer of groundwater resources in arid and semiarid regions directly affects the system efficiency and yield production (Grafton and Hussey 2011; Fallah-Mehdipour et al. 2013). Economic, social, management, biological, environmental and engineering facets should be considered to increase the water use efficiency for food production (Hsiao et al. 2007; Jakeman et al. 2016). Recent groundwater management studies have resulted in innovations that enable farmers to increase economic productivity and water use efficiency concerning water availability. Unregulated irrigation scheduling may lead to waste of water resources or loss of yield production due to over-irrigation or water scarcity, respectively (Li et al. 2011).

Simulation–optimization modeling as a decision strategy has been applied to improve cropping patterns and water allocation in the past for different purposes (Karamouz et al. 2010; Fallah-Mehdipour et al. 2013; Abbasi et al. 2015; Soltani et al. 2016; Varade and Patel 2018). Several studies have been carried out on water, land and crop management (Karamouz et al. 2004, 2007; Abbasi et al. 2015; Singh 2015; Lalehzari et al. 2015; Lalehzari and Kerachian 2020; Lalehzari 2017), that can improve the economic indicators (Singh and Panda 2012), water use efficiency (Lalehzari et al. 2016), irrigation scheduling (Lorite et al. 2007) and cropping pattern (Fallah-Mehdipour et al. 2013). A multiobjective model for the optimal irrigation planning and obtaining the alternate plan for the available cropping pattern using *NSGAII* was developed in Iran. The result showed that water use efficiency values for melon and tomato were

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increased and the amounts of allocated water for maize and onion were decreased by increasing the water price (Lalehzari et al. 2016).

Direct measurement of actual evapotranspiration, *ETa*, as an important parameter in the evaluation of irrigation efficiency and the decision system is difficult (Akbari et al. 2007; Parsinejad et al. 2013), which is estimated by various procedures such as soil moisture balance (Vedula et al. 2005), crop water stress index (Lalehzari et al. 2016) and remote sensing (Veysi et al. 2017).

The economic efficiency of irrigation water use has been computed in terms of crop output per unit of water applied. This concept has been widely used in investment decision-making, where the desire is to maximize returns from irrigation (Turner et al. 2004). The contribution of this paper is the development of a new simulation–optimization methodology for irrigation planning under uncertainty. The uncertainty of available water is represented by fuzzy numbers and incorporated into the model structure. Allocated water as fuzzy variables are discretized into five levels, and the model's extreme responses are separately evaluated at each level. The non-dominated sorting genetic algorithm II (i.e., NSGAII) is coupled with the cropping pattern simulation model (i.e., CPSM), for analyzing the solution's uncertainty.

2 Methodology

Water resources, soil characteristics, cropping patterns and climatic conditions are components of a decision system that necessitates an integrated framework to manage the agricultural water resources. The defined mechanism requires an understanding of the interconnections of the problem components.

2.1 Conceptual Model

The schematic flowchart of the simulation and optimization models has been summarized in Fig. 1. The figure indicates the process of the conceptual model where there are three main subsets done: (1) atmosphere, water, soil and plant system are simulated by distributed data, e.g., cropping pattern, economic parameters, soil hydraulic properties, irrigation dates and frequencies, sowing dates, root depth and daily climate data, (2) water allocation optimization and (3) uncertainty analysis. Non-dominated sorting genetic algorithm and particle swarm optimization are used to find the optimal solution and domains of fuzzy programming, respectively.

Maximization of the net benefit per irrigation water as an objective function can be expressed in the following non-linear form:

$$\text{Max EEW} = \frac{\sum_{p=1}^{np}\left(\left(\sum_{s=1}^{ns}(\text{BM}\times\text{HI}\times A)_s\right)_p \times B_p - \left(\sum_{s=1}^{ns}\left(\left(\text{CC}+10\sum_{i=1}^{nt} I_i \times \text{IWP}\right)\times A\right)_s\right)_p\right)}{\sum_{p=1}^{np}\left(\sum_{s=1}^{ns}\left(10\sum_{i=1}^{nt} I_i\right)_s\right)_p} \tag{1}$$

where EEW is the economic efficiency of irrigation water (IRR m^{-3}) (1 USD = 42,000 IRR); BM is the dry above-ground biomass (kg ha^{-1}); HI is the harvest index; *B* is the selling price of the crop *p*; CC is the constant costs (IRR ha^{-1}); *A* is the cultivated area (ha); IWP is the irrigation water price (IRR m^{-3}); *I* is the irrigation depth or allocated water as a decision variable (mm); *nt* is the number of growth days within the growing season of crop *p*; *np* is the number of crops; *ns* is the number of irrigation systems. Maximization of EEW is subject to the following equations:

It is assumed that the existing cropping pattern has been set based on the past experiences. Hence, this model does not need to change the total cultivated areas. However, the summation of the allocated land to each cropping pattern or plant must not exceed the existing cultivated area in the plain.

$$\sum_{p=1}^{np} A_p = A_a \tag{2}$$

where A_a is the maximum accessible area of agricultural activities. Dry above-ground biomass production is obtained from the ratio of the daily crop transpiration over the potential evapotranspiration for that day (Hsiao et al. 2007):

$$\text{BM} = \text{WP}^* \sum_{i=1}^{nt}\left(\frac{\text{Tr}}{\text{ET}_o}\right) \tag{3}$$

where Tr is the daily transpiration (mm); ET_o is the daily potential evapotranspiration (mm) which is estimated using Penman–Monteith equation. Water stored in the root zone for each time steps is given by:

$$S_{i+1} = S_i + I_i + R_i - E_i - \text{Tr}_i - \text{DP}_i - \text{RO}_i \text{ for } i = 1, 2, \ldots, nt \tag{4}$$

where *S* is the stored water in the root zone (mm); *E* is the evaporation (mm); RO is the runoff (mm); DP is the deep percolation (mm). The irrigation requirements of all the crops must be satisfied by Eq. 5 during the growing stages.

$$S_i \le I_i + R_i \le \text{FC for } i = 1, 2, \ldots, nt \tag{5}$$

where FC is the water level in the field capacity point. Benefit per cost, BPC, and allowable discharge, AW, values, BPC, should be greater than or equal to the predetermined limits for each crop or farmer:

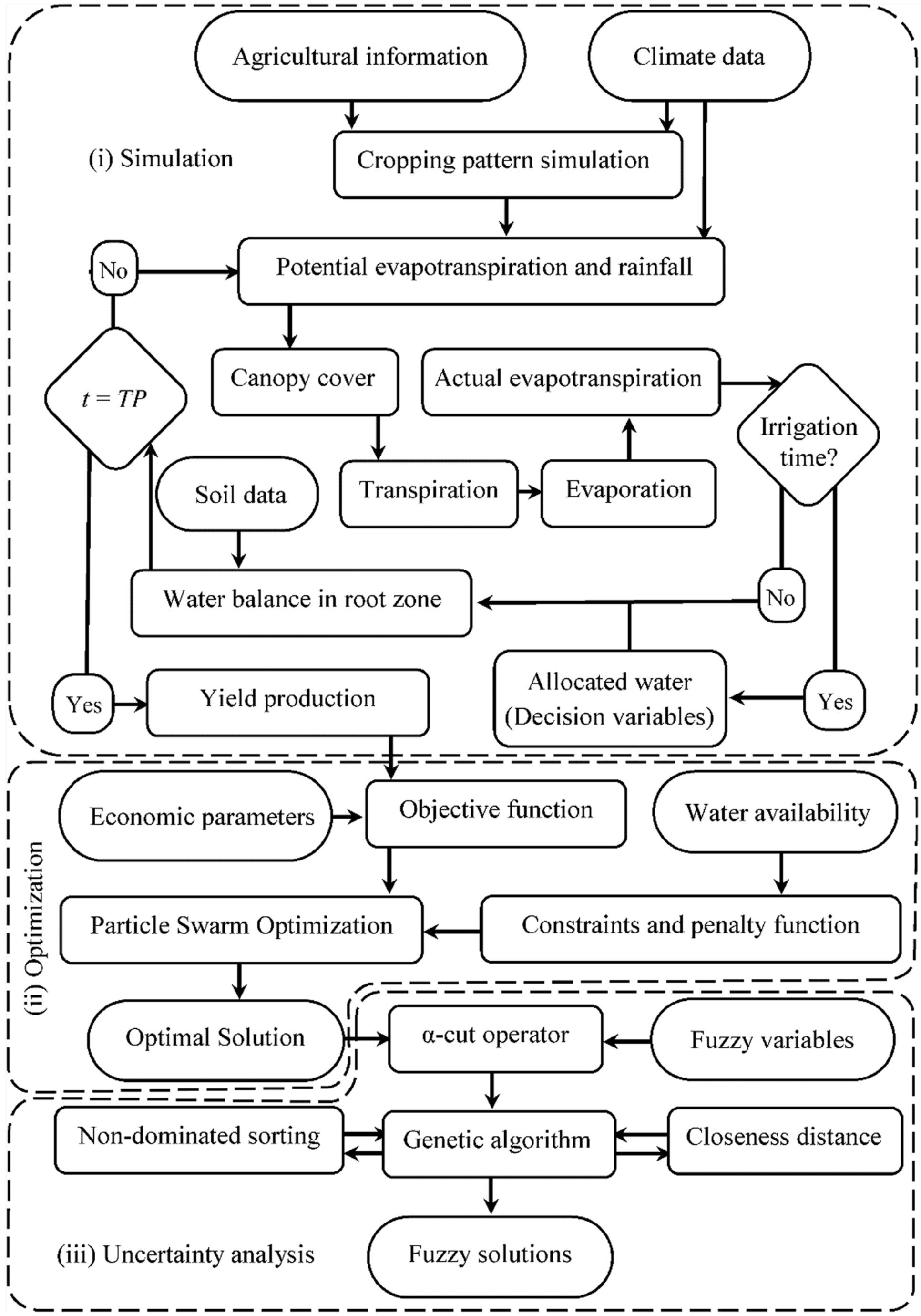


Fig. 1 A flowchart of the proposed simulation–optimization methodology

$$\mathrm{BPC}_p \geq \mathrm{BPC}_c \text{ for } p = 1, 2, \ldots, np \tag{6}$$

$$\sum_{p=1}^{np}\left(\sum_{i=1}^{nt} I_i\right) \times 10A_p \leq \mathrm{AW} \tag{7}$$

where BPC_p and BPC_c are obtained and expected benefits per cost for crop p.

The particle swarm optimization (PSO) is a search-based optimization method that has been used to search the optimal solutions of the above-mentioned mathematical model. PSO consists of a swarm of particles as the potential solutions which are inspired by social behaviors of fish schooling or birds flocking (Shi and Eberhart 1999).

2.2 Fuzzy Analysis

In this study, the α-cut decomposition method has been used for handling the triangular normalized fuzzy number to represent uncertainty in the allocated water. According to Fig. 1, a multiobjective optimization problem is required to find the minimum and maximum points of solution for each α-cut (Nikoo et al. 2013). The non-dominated sorting genetic algorithm abbreviated as NSGA is one of the fast evolutionary techniques and is utilized to arrange the optimal solutions in the Pareto front for solving an optimization problem with two or more objective functions. The process of fuzzy analyses using NSGAII (Deb et al. 2002) is started by randomly generating an initial population of solutions. The population is stored in different fronts using the non-domination sorting method. In this method, the first level of classified fronts is called Pareto front (Lalehzari et al. 2016). A flowchart of applying the non-dominated sorting concept for uncertainty analysis is illustrated in Fig. 2 for a

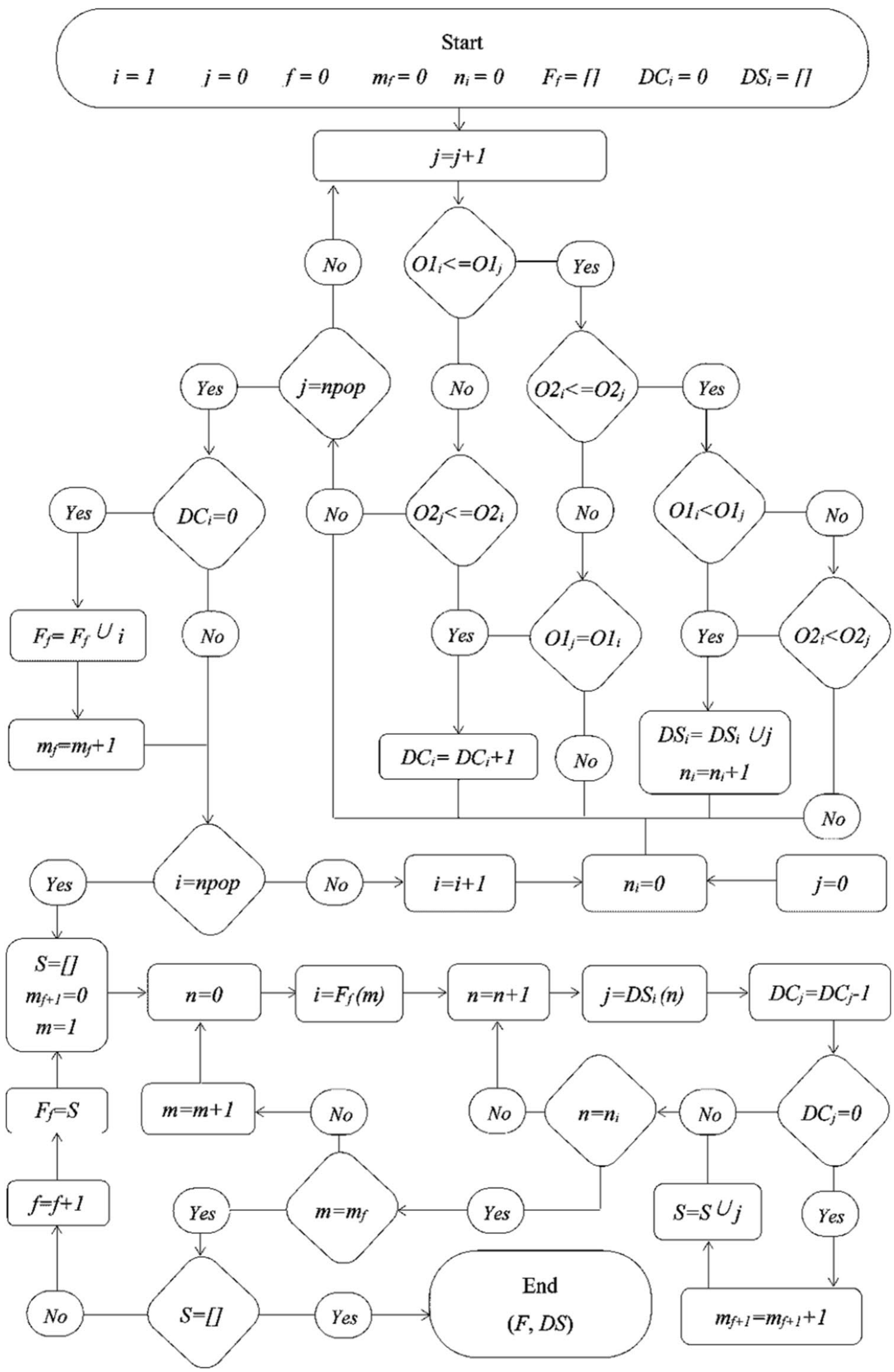


Fig. 2 A flowchart of the proposed methodology for using non-dominated sorting method in fuzzy uncertainty analysis. O_1 and O_2 = objective functions; *DC*, number of dominated solutions; *F*, optimal fronts; *DS*, non-dominated set; *npop*: number of population

two-objective function problem. As shown in the figure, the objective functions (O_1 and O_2) for each member of population (i or j) are ranked based on the non-dominated sorting theory (Deb et al. 2002) and then placed on different fronts (S) according to the rank obtained. Finally, the flowchart output is stored in two categories of information including the non-dominated set (DS) and the front number of each solution (F).

Closeness-distance, CD, is evaluated by Eq. 8 to increase the distance of solutions in every front instead of the crowding-distance equation used in the standard NSGAII (Deb et al. 2002; Haghighi and Zahedi-Asl 2014):

$$\mathrm{CD}_i = \sum_{m=1}^{2} \frac{\mathrm{OF}_m^i - \mathrm{OF}_m^{\min}}{\mathrm{OF}_m^{\max} - \mathrm{OF}_m^{\min}} \tag{8}$$

where OF_m^i is the objective function value m for the solution i ($i=1$ to N); and, $\mathrm{OF}_m^{\max}$ and $\mathrm{OF}_m^{\min}$ are the maximum and minimum values of the objective function ($m=1$ to $M=2$), respectively.

2.3 Study Area

Shahrekord plain lies in 32° 07″–32° 35″ N latitude and 50° 38″–51° 10″ E longitude located at Chaharmahal and Bakhtiari Province, Iran (Fig. 3). Annual mean precipitation is approximately 120 mm year^{-1}, which corresponds to semiarid conditions. Uncontrolled heavy pumping of groundwater (about 250 MCM annually) has caused over-exploitation in the irrigated lands (Tabatabaei et al. 2010; Fakharinia et al. 2012; Lalehzari et al. 2013, 2014; Lalehzari and Tabatabaei 2015).

The required data for simulating the cropping pattern, e.g., economic parameters, sowing dates, soil properties, water availability and details of existing cropping patterns are considered as inputs for exploring the optimal water management scenarios. More details are presented in Table 1. The information has gathered during the period of 2016–2017, and the PSO has been used for the irrigation planning.

3 Results and Discussion

The simulation–optimization model was run for the three selected crops (colza, barley and wheat) during winter, nine selected crops (tomato, potato, onion, cucumber, maize, sugar beet, lentil, chickpea and bean) during monsoon, and alfalfa as an annual crop. Optimal allocated water, yield production, net benefit, water productivity and relative water use efficiency are presented in Table 2. The results of the developed optimal irrigation planning model indicate that the net annual benefit from the cropping pattern has been increased to 182,625 million IRR comparing to the existing 67,583 million IRR. Hence, there is an increase of 43.14% or 55,042 million IRR in the net annual return. This is due to the reduced water allocation to wheat and barley and alfalfa crops and increased water allocation to tomato, potato and onion crops. A similar water allocation plans have been suggested for the arid and semiarid regions (Alvarez et al. 2004; Noory et al. 2012; Fallah-Mehdipour et al. 2013; Montazar 2013; Lalehzari et al. 2016).

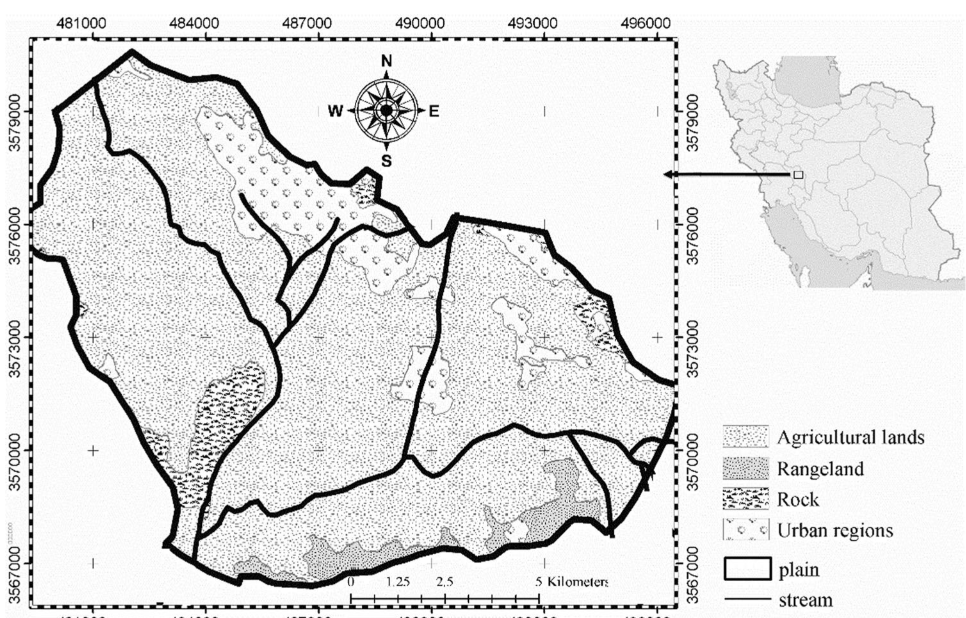


Fig. 3 Landuse map of the study area in Iran

Table 1 The components of the existing cropping pattern in Shahrekord plain

Crops	Cultivation area		Max yield	Benefit	Constant cost	Water demand
	ha	%	kg ha^{-1}	IRR kg^{-1}	1000IRR ha^{-1}	m^3 ha^{-1}
Wheat	1360.2	29.13	4142	11,273	22,489	3900
Barley	591.4	12.66	3916	9111	20,691	3870
Tomato	3.9	0.08	32,786	9315	82,805	6230
Potato	714.7	15.30	31,922	810	86,843	5300
Onion	1.1	0.02	34,667	1180	72,237	9100
Cucumber	10.5	0.22	28,355	9946	63,801	7200
Colza	31	0.66	3269	25,300	21,750	4500
Lentil	9.5	0.20	2188	31,337	21,884	3700
Chickpea	3.3	0.07	2233	53,231	22,755	6000
Bean	178.7	3.83	3326	54,554	32,160	6400
Sugar beet	89.6	1.92	28,487	5077	44,400	8200
Maize	529.1	11.33	24,959	4209	27,787	7600
Alfalfa	1146.9	24.56	18,064	4276	23,720	4400

Table 2 Optimal planning of cropping pattern in Shahrekord plain

Crop	Water allocated		Yield production	Net benefit	Water productivity	Relative water use efficiency
	m^3 ha^{-1}	%	kg ha^{-1}	10^{4}IRR ha^{-1}	kg m^{-3}	–
Wheat	3605	92.4	3774	1343	1047.0	0.99
Barley	3611	93.3	3457	415	957.1	0.95
Tomato	6256	86.5	27,359	16,125	4373.0	0.96
Potato	4514	85.2	25,247	10,888	5593.5	0.93
Onion	9091	99.9	34,091	31,602	3750.0	0.98
Cucumber	6895	95.8	20,410	12,767	2959.9	0.75
Colza	4252	94.5	2813	4218	661.6	0.91
Lentil	3316	89.6	1821	2824	549.2	0.93
Chickpea	5242	87.4	1606	5412	306.4	0.82
Bean	5810	90.8	2713	10,644	467.0	0.90
Sugar beet	9554	85.3	21,533	5125	2254.0	0.89
Maize	7309	85.0	21,174	5061	2897.0	1.00
Alfalfa	4321	98.2	16,643	861	3851.7	0.94

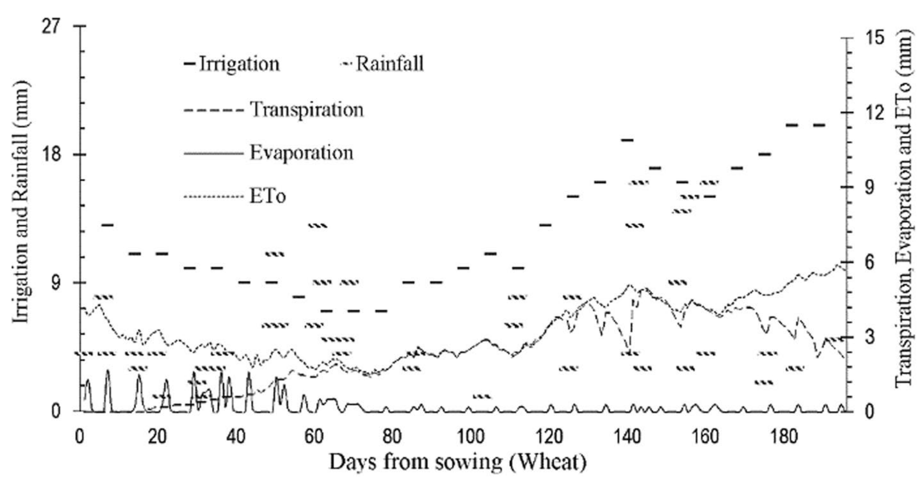


Fig. 4 Optimal irrigation planning for wheat

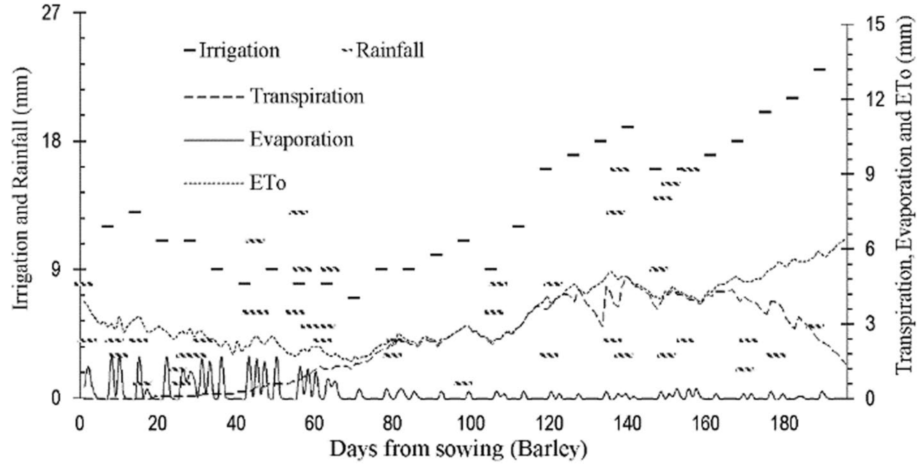


Fig. 5 Optimal irrigation planning for barley

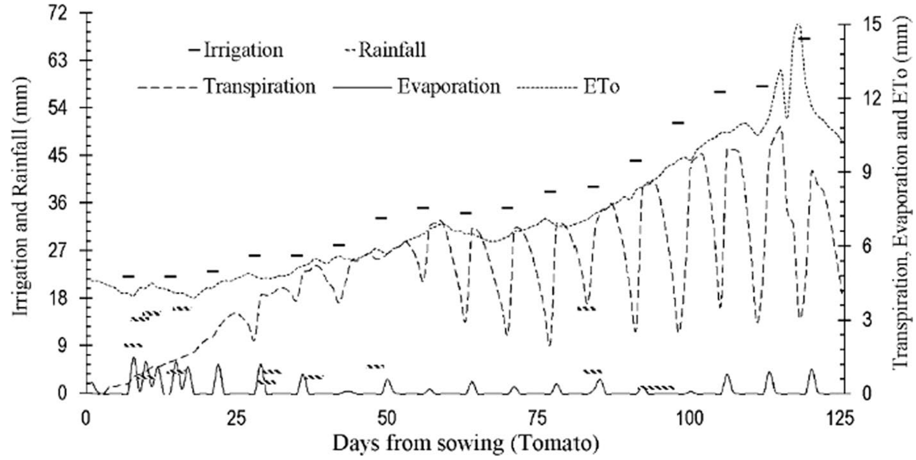


Fig. 6 Optimal irrigation planning for tomato

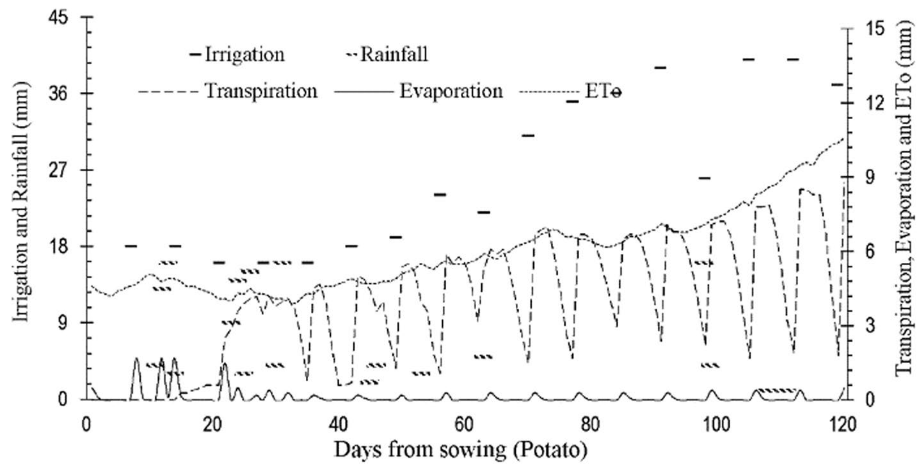


Fig. 7 Optimal irrigation planning for potato

Figures 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15 and 16 show the optimal irrigation planning compared to potential evapotranspiration, transpiration, evaporation and rainfall for different plants of the cropping pattern considering all constraints and soil water balance. Water requirement in the development and senescence stages of the green canopy throughout the crop cycle is less than potential evapotranspiration. The maximum percentage of water requirement is supplied at the stage of maturity canopy cover during the end of the development period to the beginning of senescence

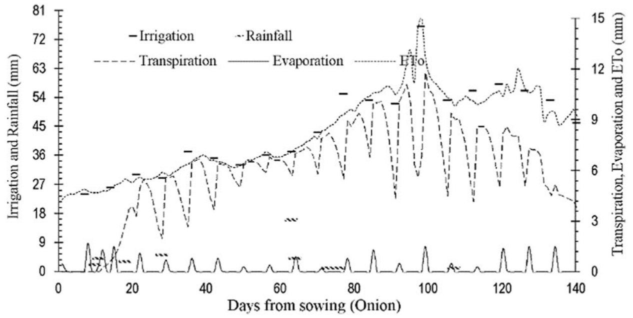


Fig. 8 Optimal irrigation planning for onion

time. As shown in figures, the rate of transpiration changes relative to irrigation intervals is considerable, especially in spring crops. Moreover, it seems that the irrigation events should be decreased for wheat, barley and colza. Therefore, deficit irrigation strategies can be taken into account to reach acceptable irrigation policies regarding the characteristics of these crops (Alvarez et al. 2004; Huang et al. 2012).

At the end of optimization, the optimal solution is selected to obtain the fuzzy responses of the objective function according to the computation of five levels of $\alpha=0$, 0.25, 0.5, 0.75 and 1 introduced to the input variables. According to the described procedure presented in Fig. 1, in each α-cut, the NSGAII must optimize 26 objective functions simultaneously.

Fuzzy EEWs corresponding to the uncertainty in the decision variables (dash line) based on the various levels of α-cut is illustrated in Fig. 17. The maximum optimal values of EEW have been obtained 34.63, 25.76 and 24.12 10^3IRR m^{-3} for onion, tomato and potato, respectively.

Investigating the sensitivity of the net benefit and water productivity to changes in water allocated in nine predetermined α-cut are summarized as S_1, S_2, …, S_9 are shown in Figs. 18 and 19. Input uncertainties are spread out on the cropping pattern are shown in the illustrated figures. Onion, tomato and cucumber have obtained an increased volume of irrigation water, respectively. As it is rationally expected, the crops with more yield production are more

Fig. 9 Optimal irrigation planning for cucumber

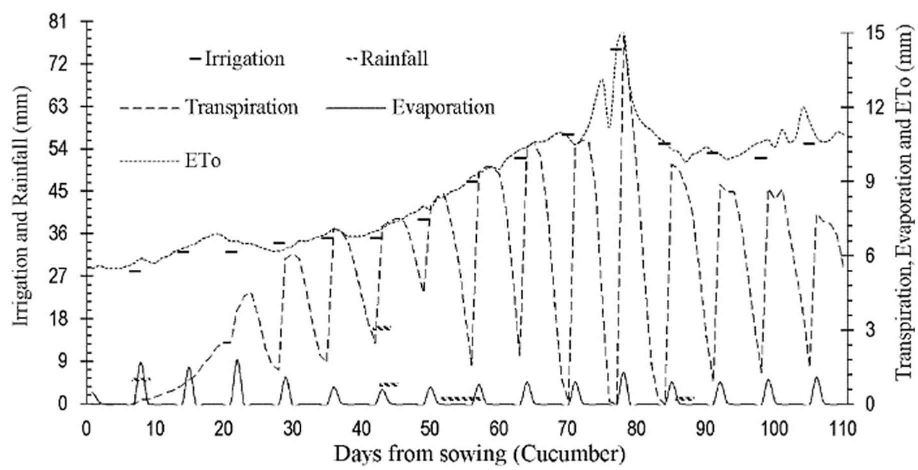
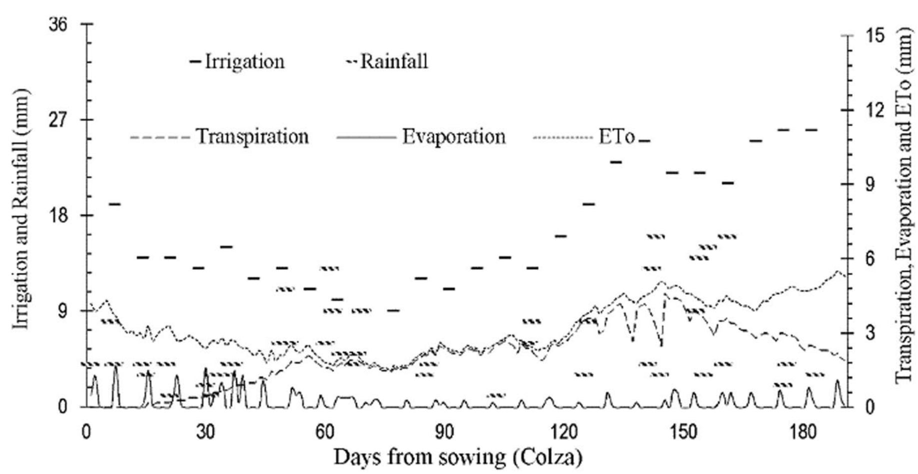


Fig. 10 Optimal irrigation planning for colza



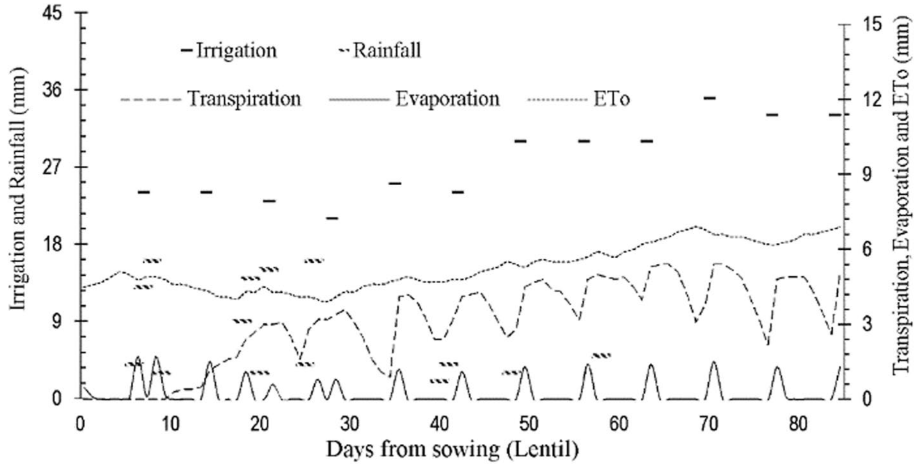


Fig. 11 Optimal irrigation planning for lentil

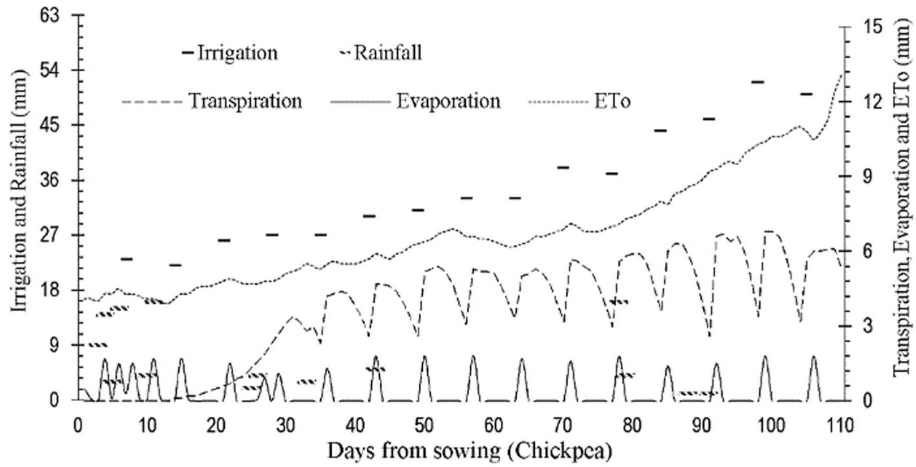


Fig. 12 Optimal irrigation planning for chickpea

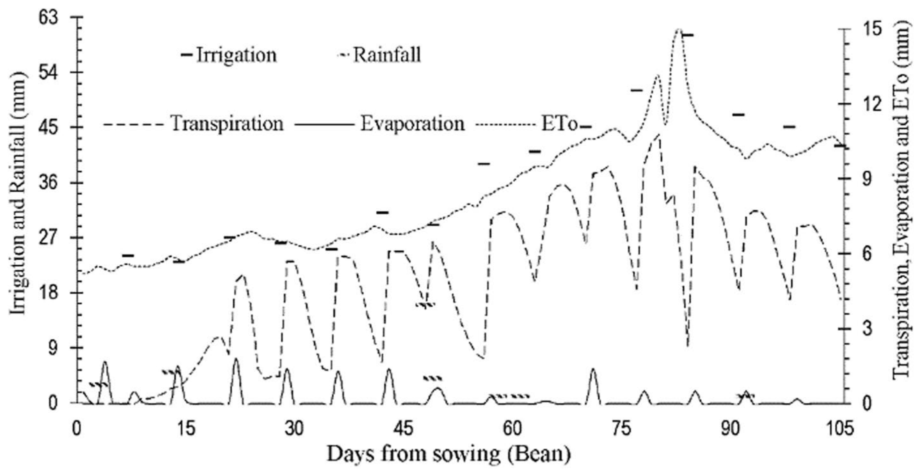


Fig. 13 Optimal irrigation planning for been

affected by uncertainty, while the winter crops like wheat, barley and colza are more resistant to the input uncertainties. Reducing the water allocated to the critical stress level of the crop increases water productivity (Fig. 19). Furthermore, an increase of 25% in the amount of allocated water has reduced the water productivity by 1.87, 1.2 and 1.06 kg m^{-3} for potato, tomato and onion, respectively.

Figure 20 presents the extreme values for the fuzzy relative water use efficiency, RWUE. In the most general sense, RWUE refers to the ratio of the amount of water used to

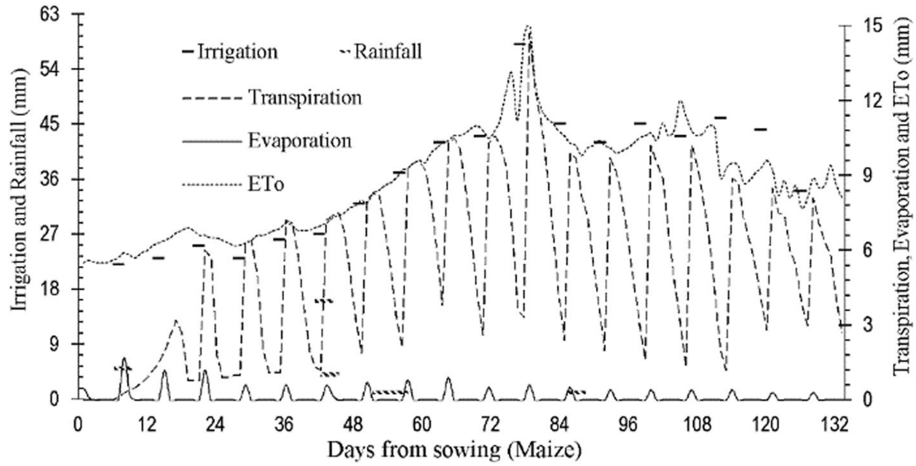


Fig. 14 Optimal irrigation planning for maize

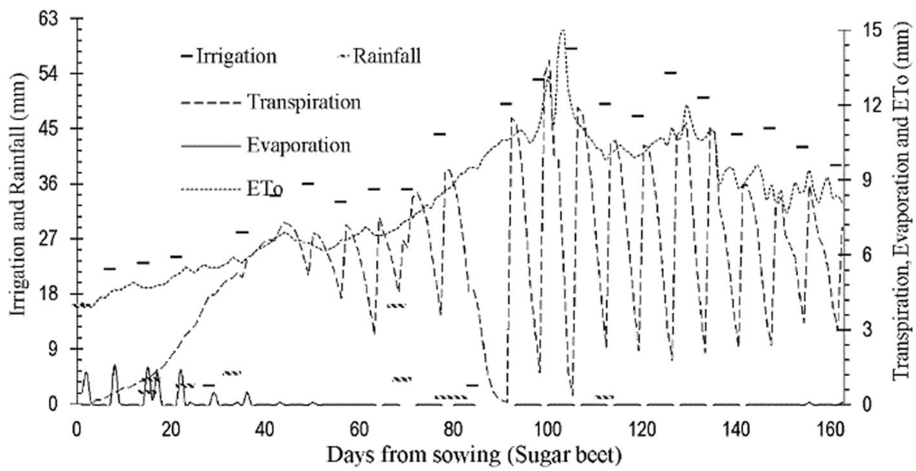


Fig. 15 Optimal irrigation planning for sugar beet

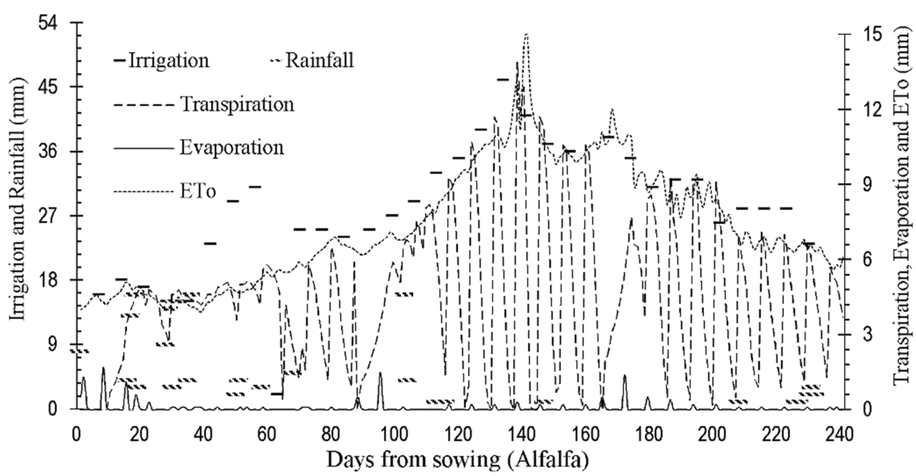


Fig. 16 Optimal irrigation planning for alfalfa

achieve yield production. The maximum values of relative water use efficiency are 1, 0.99 and 0.98 for maize, wheat and onion, respectively. Among the other crops, the minimum crisp value of RWUE is 0.75 for cucumber. The minimum values of fuzzy RWUE corresponding to the optimal solutions are 0.310, 0.302, 0.295 and 0.287 for potato, maize, tomato and lentil, respectively. The maximum values of fuzzy RWUE which are less than crisp values have been computed for wheat, barley, tomato, onion and maize,

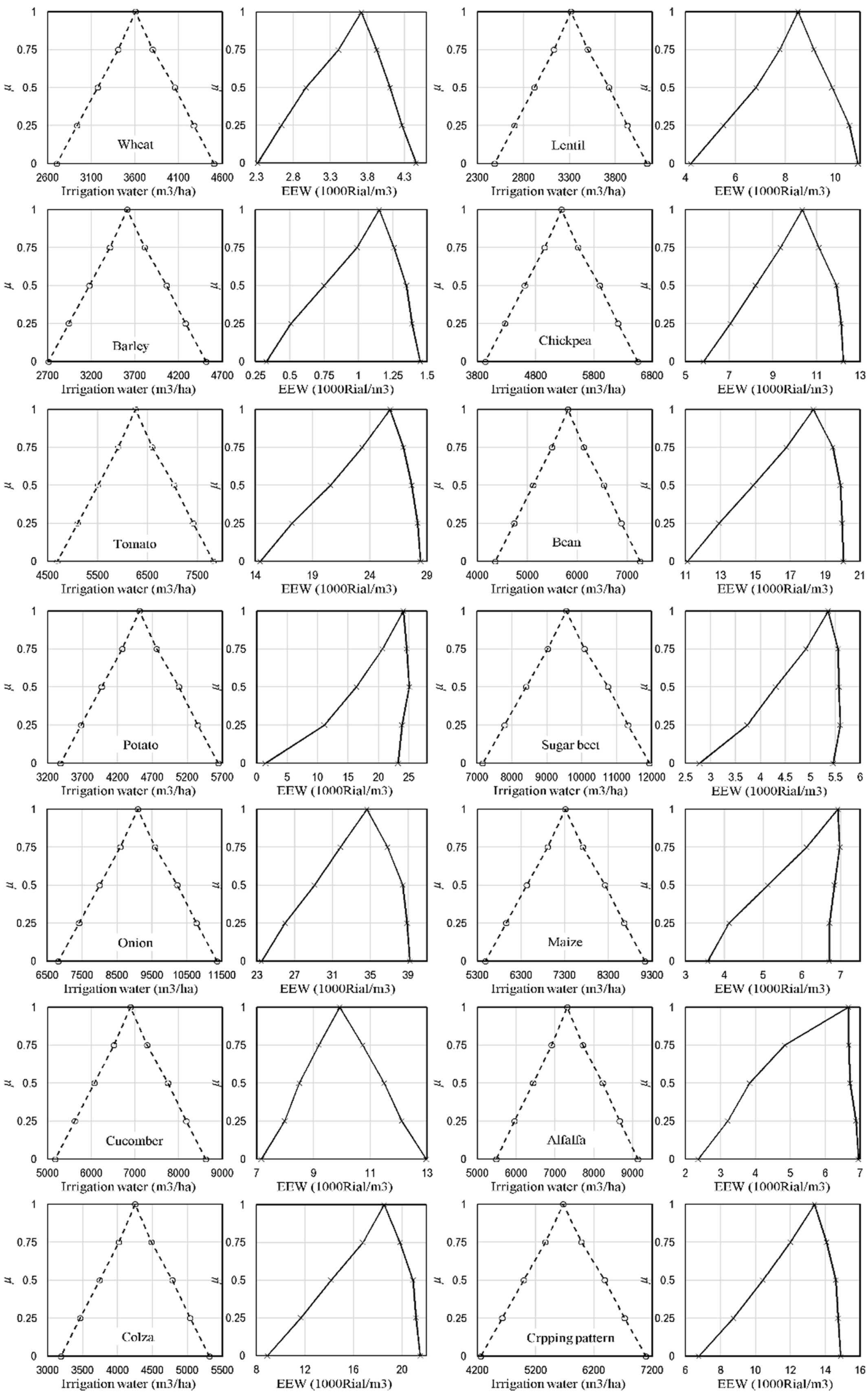


Fig. 17 Membership function of the fuzzy solutions

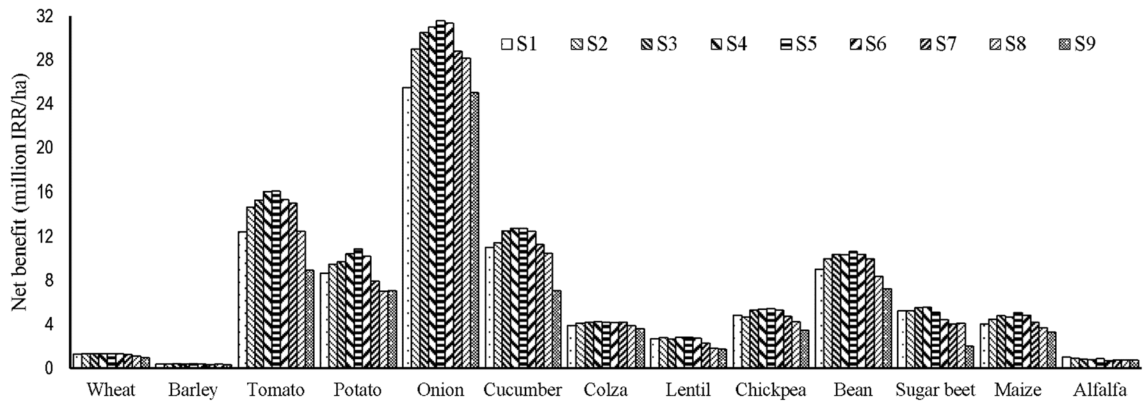


Fig. 18 Uncertainty analysis in the net benefit

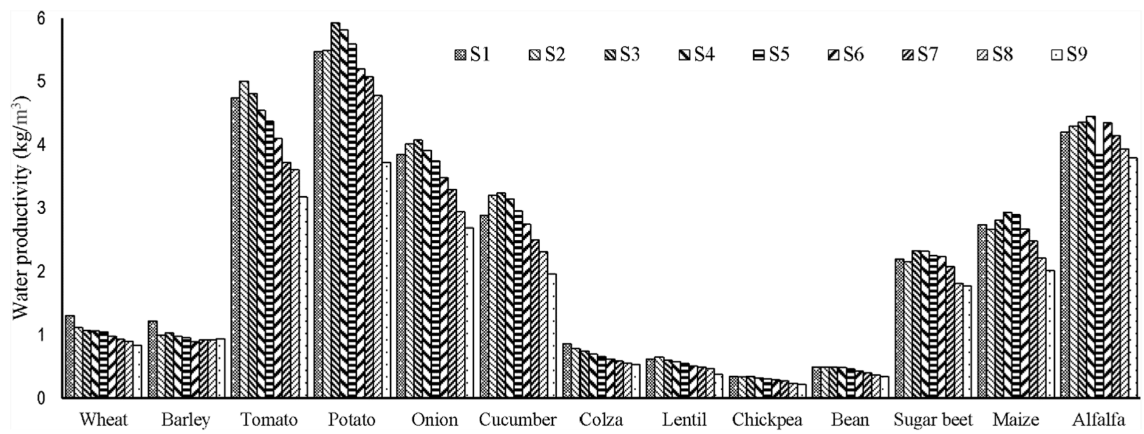


Fig. 19 Uncertainty analysis in water productivity

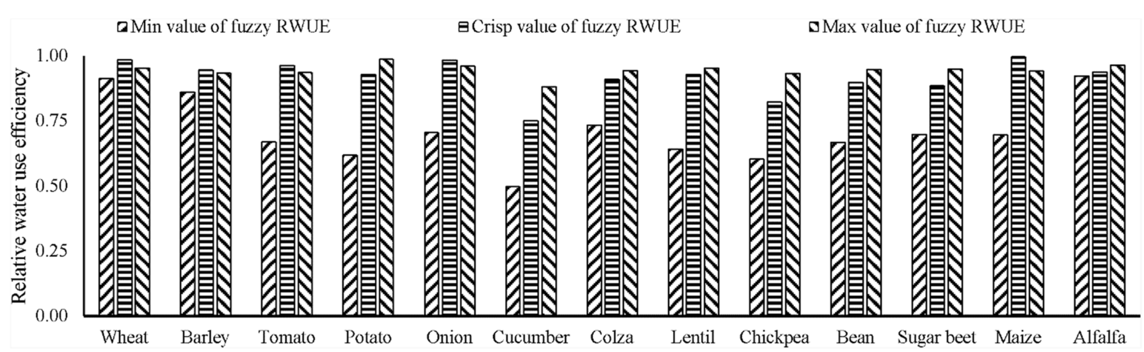


Fig. 20 Maximum uncertainty in the relative water use efficiency

respectively. This is based on this fact that the most part of water demands of these crops have been supplied.

4 Summary and Conclusion

This paper presented a new methodology based on the fuzzy set theory for developing optimal irrigation planning policies. In this methodology, the concept of economic efficiency was considered as the objective function (i.e., maximizing the total net benefit of crop production). The developed simulation model takes into account the soil types and soil moisture conditions in the root zone for each crop. The constraints set includes the economic parameters, soil water balance of the cultivated area, and the effects of the water stress on the canopy cover and the net biomass production. The maximum values of the economic efficiency of irrigation water and relative water use efficiency have been estimated as 34,630 IRR m^{-3} and one for onion and maize, respectively. The results showed that an increase of 25% in the amount of allocated water has reduced the water productivity by 1.87, 1.2 and 1.06 kg m^{-3} for potato, tomato and onion, respectively. Furthermore, optimum irrigation strategies to explore managerial implications were suggested for increasing yield production in the interest of farmers. It can help beneficiaries to improve regional farming economic benefits and water productivity. This methodology especially with daily crop growth simulation could help decision-makers to define sustainable irrigation policies. Assuming a constant irrigation period for each crop is the main limitation of this study. The impacts of this assumption should be evaluated in future studies.

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