Mathematical Programming Approaches for Modeling a Sustainable Cropping Pattern under Uncertainty: A Case Study in Southern Iran

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Mathematical Programming Approaches for Modeling a Sustainable Cropping Pattern under Uncertainty: A Case Study in Southern Iran

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Abstract

In recent years, the excessive and unreasonable use of chemicals, the occasional use of water, and the use of improper irrigation methods have created a worrying and unstable situation in developing countries' agricultural activities. In the present study, the robust multi-objective fractional linear programming model (RMOLFP) was introduced to determine the sustainable optimal cropping pattern. This model was presented in the Gotvand irrigation and drainage network located in Khuzestan province, southern Iran, under two scenarios with and without considering the uncertainty to evaluate the ability of the model. The results showed that in the first scenario, the consumption of critical disruptive inputs of sustainable agriculture such as fertilizers and chemical pesticides decreased by 5.9% and 8.19%, respectively. On the other hand, the model's uncertainty condition was applied in the second scenario in which the increase in gross margin was reduced. There is a trade-off between protecting the optimization model against system uncertainty and gross margin. Finally, the ability of the proposed model to apply uncertainty conditions was verified by the Monte Carlo simulation method. The results of this simulation confirmed the use of the RMOLFP method in determining the sustainable optimal cropping pattern for the study area.

Keywords: Sustainable Cropping Pattern, Uncertainty, Robust Optimization, Controlled Estimation Method, Khuzestan.

Subject classification codes: C02, C61, C83, Q1, Q56.

1. Introduction

Over the last five decades, agricultural development policies have increased agricultural production; however, the use of disruptive inputs such as pesticides, fertilizers and agricultural machinery has gradually replaced natural resources available inside farm M. Li et al. (2020). The issue of sustainable agriculture has been emphasized by numerous international organizations and has led to positive environmental, economic and social impacts (Tseng, Chiu, Tan, & Siriban-Manalang, 2013). Due to the economic perspective, the emphasis on sustainable production has been increasing agricultural inputs' productivity and improving and diversifying market opportunities (M. Li et al., 2020).

One of the approaches to achieve the optimum use of off-farm inputs and disrupt the sustainable agriculture process is to determine the optimum utilization of inputs by establishing a sustainable optimal cropping pattern (X. Li et al., 2017). Figure 1 shows the main purposes of studies that focus on the sustainable production aspect of agricultural products also implicitly consider other objectives of crop pattern studies. The explanation for this claim lies in the definition of sustainability provided in Guideline 21 at the United Nations Conference of Environment and Development (UNCED) in 1992. In this definition, sustainability was presented in ecological, economic and social dimensions (Mardani Najafabadi, Abdeshahi, & Shirzadi Laskookalayeh, 2020).

Ecological sustainability means maintaining the ability of the system to adapt to the environment fully and its changes. Therefore, Studies focusing primarily on environmental considerations emphasize this aspect of sustainability (Mardani Najafabadi, Ziaee, Nikouei, & Ahmadpour Borazjani, 2019). Sustainability in the economic dimension is a crucial concept in sustainable development literature. One of the most important objectives to be achieved in this dimension is to increase farmers' gross profit. In most developing countries, the agricultural sector tends to increase agricultural output while reducing unemployment (Mardani, Ziaee, & Nikouei, 2018). This is due to the country's food security and the reduction of the adverse social effects of unemployment (Mardani Najafabadi et al., 2019). Thus, the two remaining goals (food security and employment) can be considered in the social dimension of sustainability.

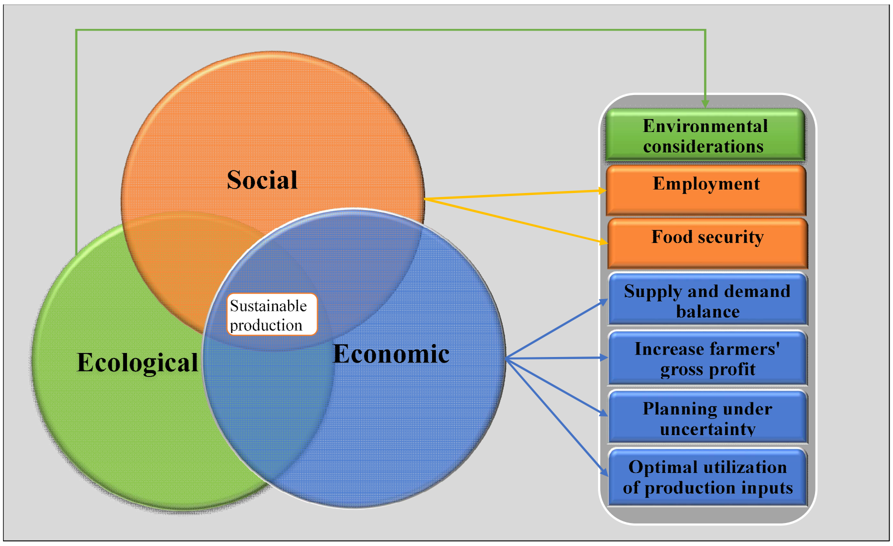

Figure 1. Tree dimensions of sustainable optimal cropping pattern

Considerable studies have been carried out to optimize the allocation of arable land using mathematical programming techniques in different regions of the world. Most of the studies have used linear programming models (Wineman & Crawford, 2017), goal programming (Mardani, Esfanjari Kenari, Babaei, & Asemani, 2013) and multi-objective programming (Ren, Li, & Zhang, 2019).

On many practical issues such as quantitative sustainability indicators, optimizing the ratio of criteria than each criterion alone provides a better vision (Mardani Najafabadi et al., 2020). Fractional programming is the most common mathematical programming with relative objectives. On the other hand, the existence of different criteria in relational objectives have also led to the development of multi-objective linear fractional programming models. This approach has been used in various studies in agricultural management. For example, in the study of Zhang et al. (2017), the GFCCFP method was used to optimally allocate irrigation water in the Heihe basin in northwest China. CONNISE method has been used in their study to find optimal solutions. This method is defined based on the estimation of weak efficient boundaries in the objectives space, including some points of feasible set (Gorissen, 2015). The distance between these points should not exceed the value previously provided. This method is beneficial for finding efficient solutions, but in problems with more than two objectives, the optimal solutions lose their convergence, and the final solution is challenging to find. This problem can be solved by controlling the distance considered for a predetermined error using the Controlled Estimation Method (CEM) method proposed by Caballero and Hernández (2004).

The agricultural uncertainties are traditionally classified in areas such as production management, marketing and investment (Mardani Najafabadi et al., 2020). The application of fractional programming under uncertainty in agricultural management is widespread. In the meantime, the use of fuzzy, interval, gray, stochastic or a combination of these methods are more common (Tan & Zhang, 2018; Wang, Liu, Guo, Yue, & Guo, 2019).

In the mid-1990s, the issue of creating conservatism in mathematical programming models was introduced by limiting uncertain parameters (Ben-Tal & Nemirovski, 2000). The benefits of using robust optimization are reporting point-based optimal solution (confronting the optimal interval solutions in interval programming) (M. Sabouhi & Mardani, 2017) and lack of awareness of the data distribution (the challenge of coping with the need to be aware of the data distribution in the stochastic programming) (Mardani Najafabadi & Taki, 2020).

Recently, a wide range of robust optimization applications in the management of water resources and agricultural land have been implemented. For the first time, this method was used in fractional programming by Gorissen (2015). Tan and Zhang (2018) optimized the allocation of water resources and agricultural land using robust fractional programming to increase water-use efficiency in the arid northwest region of China. It should be noted, however, that in both studies, single-objective fractional programming is considered, and the problem of drastically losing the convergence of the optimal solutions in multi-objective fractional programming in their methods remains. Using CEM can be an appropriate approach to address this defect and enable the application of robust multi-objective fractional programming to provide a sustainable optimal cropping pattern.

Gotvand irrigation and drainage network is located in southwestern Iran in Khuzestan province. According to official statistics from government agencies, fertilizer and pesticides used in the lands covered by this network is 3.6 times the average in Iran (Anonymous, 2018). The surplus irrigation water in the network is returned to the rivers by drainage, contaminate water with a surplus of fertilizers and pesticides in downstream of the network (Mardani Najafabadi et al., 2020). Due to the mentioned issue, selecting this region to determine the cropping pattern that leads to optimal use of disturbing inputs to sustainable agriculture, seems appropriate. Besides, the irrigation water consumption is better managed in this network.

Therefore, the purpose of the present study was to propose a mathematical programming model to determine the sustainable optimal cropping pattern for the Gotvand irrigation and drainage network covered land. For this purpose, a robust multi-objective fractional linear programming model (RMOLFP) was proposed. Thus, the innovation and importance of this study can be examined in two respects; first, a new mathematical programming model for optimal cropping pattern with emphasis on sustainability has been proposed, and second, a detailed plan has been prepared for an area that desperately needs a revision of the cropping pattern.

2. Methodology

2.1 Study Area

Gotvand irrigation and drainage network is designed for irrigation of land in three areas of Gotvand, Aghili and Dimcheh, confined between two rivers, Karoun and Lor (Figure 2). The purpose of this network was to manage water resources better and distribute the water equitably among the farmers in the area. The land covered by this network is 43930 hectares, of which 34144 hectares with over 4300 plots are used. This irrigation network directs irrigation water to 1,076 plots of land in the Gotvand region, using 56 km of canals and 121 active valves with an average discharge of 68 m^3/s.

Aghili area is smaller so that by using 44 km of canals and 165 active valves, 11.23 m3/s of irrigation water can irrigate 1118 plots of land. Both Gotvand and Aghili regions receive their required irrigation water from the Gotvand Dam constructed on the Karoun River. The most considerable amount of infrastructure is in the Dimecheh area. The length of the canals in this area is 179 km and uses 241 valves to deliver 43 cubic meters of river water to 2006 arable land. In addition to the Gotvand Dam, the Dimcheh area feeds directly on several alternative dams from the Lor River, a tributary of the Dez River (Anonymous, 2017).

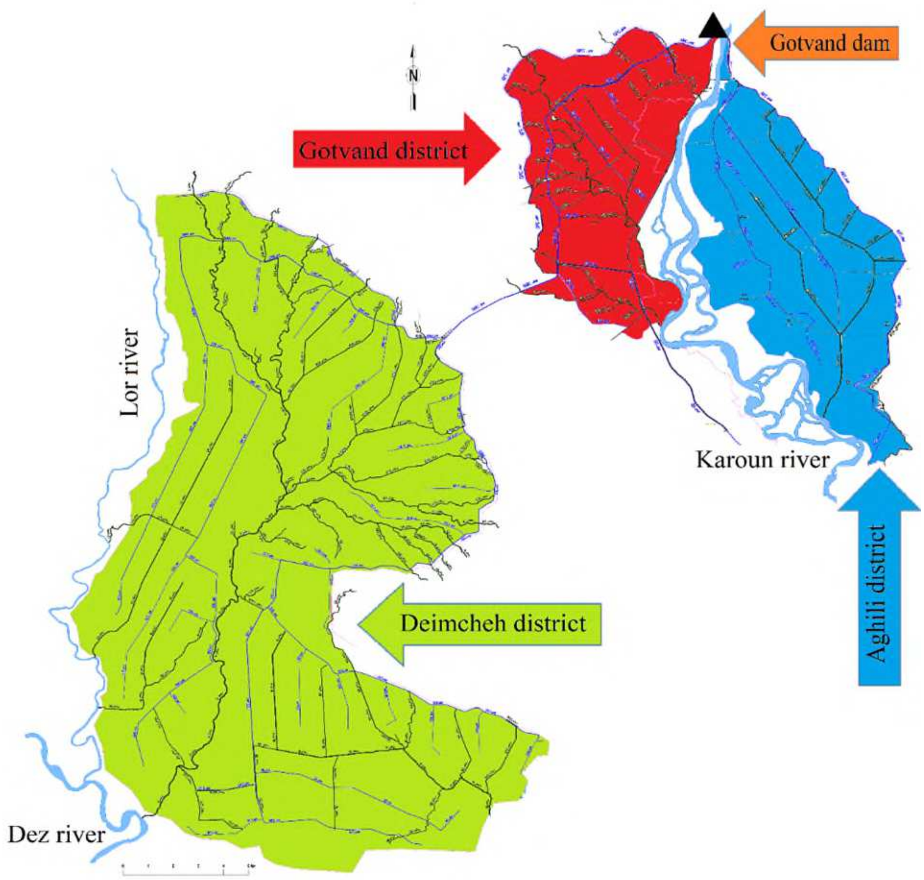

Figure 2. Schematic of the Gotvand irrigation and drainage network

2.2 Multi-objective Fractional Linear Programming

Fractional linear programming is a type of fractional programming, and the numerator and denominator of the objective function is affine Function (AF), and the possible set is a convex polyhedron. A multi-objective linear fractional programming is presented as Eq. (1):

$$Max \qquad \left\{ \varphi_1(x) = \frac{c_1^t x + \alpha_1}{d_1^t x + \beta_1}, \ldots, \varphi_p(x) = \frac{c_p^t x + \alpha_p}{d_p^t x + \beta_p} \right\} \tag{1}$$

$$s.t. \qquad Ax \le b,$$

$$x \ge 0,$$

Where c and d are the coefficients of the objective function, α and β are the constant components, A is the technical coefficient matrix, x is the decision variable, and b is right-sided values. The CONNISE method, which combines the constraint method (CON) and the Non-inferior Set method

(NISE), can be used to find optimal solutions to multi-objective optimization problems. This method is also used for multi-objective fractional linear programming.

Assuming that in multi-objective programming, E is efficient set while E^w is weak efficient set. The CONNISE method is defined based on the estimation of weak efficient boundaries including points of the set of possible zones in the objective space ($\varphi\left(E^w\right)$). The distance between possible points should not exceed a certain value.

Although the CONNISE method was very useful for finding efficient solution but in problems with more than two aims, the solutions lose their convergence so finding the final solution is very difficult. This problem can be solved using the Controlled estimation method (CEM). In this method, the intended interval for the predetermined error is controlled. The CEM algorithm which is consists of 7 steps, proposed by Caballero and Hernandez (2004).

In the first stage, the ideal and non-ideal points (the pay-off matrix) are obtained. The boundaries of objective space are formed between ideal (D_i^*) and non-ideal (D_{i-}) values. In the second stage, $\varepsilon = \max_{i=1,\ldots,p} \left|\varphi_i^* - \varphi_{i-}\right|$, is calculated, where φ_i^* and φ_{i-} are ideal and non-ideal values in the objective space, respectively. At this stage, acceptable percentage of error for the interval between possible points (*d*) is considered by the decision maker and finally, $\delta = \frac{1}{d}$ is calculated. Then, $s=\varnothing$ and $A=\varnothing$ sets are defined that s is points of current estimation and A is loose points. In the third stage, m=E($\frac{1}{d}$) is calculated in which E($\frac{1}{d}$) is integer part of $\frac{1}{d}$. By using Parametric Constraints Method (PCM) and m number, set *s* iteration is achieved.

In the fourth stage $\theta = \alpha\delta$ is calculated where $\alpha \in \left[0,1\right]$, assume that s=$\left\{x^1,\ldots,x^k\right\}$, K=1,…,N, and K$\neq$J. If for any *i=1,…,p*, $\left|\varphi_i\left(x^j\right) - \varphi_i\left(x^k\right)\right| < \theta / \left|\varphi_i^* - \varphi_{i-}\right|$, inequality is established, x^k point is eliminated from *S* set. This process will continue until many points left in the set *S*. This step is known as the filtering step. In the fifth step, it is assumed that s=$\left\{x^i,\ldots,x^N\right\}$ and for each x^j, *J=1,…,N*, the endpoint (x^k) corresponding to (x^j) is found in the objective space. If $\max_{i=1,\ldots,p} \left|\varphi_i\left(x^j\right) - \varphi_i\left(x^k\right)\right| > d\varepsilon$, x^j is unstable point and then x^j is placed in set A. This stage is repeated for all x^j . If A is null, this process is over, otherwise the sixth step is started and *m* that is obtained from third stage, considered as *m+1*. If A= $\left\{x^1, \ldots, x^m\right\}$, for each x^j belongs to A,considered instead x^j point, which is closer to x^k (in stage four). This stage is repeated for all points in set A. Ultimately, in stage seventh, set $A = \varnothing$ is obtained and it goes to step three.

2.3 Robust Optimization

In the present study, robust optimization applies the uncertain conditions to the proposed parameters. The linear form of the robust optimization model can be written as Eq. (2) (Ben-Tal & Nemirovski, 2000):

Maximize cx

Subject to $\sum_{j=1}^{n} \tilde{a}_{ij} x_j \le b_i, \qquad \forall i, j \in J_i$ (2)

$l \le X \le u.$

Where J_i is a subset of the parameters associated with the uncertain parameter $\tilde{a}_{ij}$ which is specified for each constraint *i*. Assume that $\tilde{a}_{ij}$ are independent, symmetric and their boundaries are in the range of [-1, 1].

Eq. (2) can be rewritten as robust optimization model that improves the reliability of systems under uncertainty (Bertsimas, Iancu, & Parrilo, 2010):

Maximize cx

Subject to $\overset{\mathrm{n}}{a_{ij}}\, x + B_i\left(x, \Gamma_i\right) \le b_i \qquad \forall i$ (3)

$x \ge 0$

Where

$B_i\left(x, \Gamma_i\right) = Max \sum_{j=1}^{n} x_j \hat{a}_{ij} u_{ij}$

$$Subject \quad to \qquad \sum_{j=1}^{n} u_{ij} \le \Gamma_i \qquad \forall i \tag{4}$$

$$0 \le u_{ij} \le 1$$

Where for each *j*, $y_j = \left| x_j^* \right|$. In Model (5), $\sum_i^{\mathrm{n}} a_{ij}\, x_j \le b_i$ is presents *i*th constraint in terms of certainty. This model is based on a nonlinear form of robust optimization model. The reason for the nonlinearity of this model is additional maximization expression. This maximization statement by the controlling parameter of the amount of conservatism (Γ_i) guarantees the model's reliability against uncertainty. calculating, the linear form of Model 5 is used to avoid the complexity of calculations in the maximization expression as follows (Bertsimas et al., 2010):

And finally, the form of robust optimization is model (5):

$$Maximize \qquad cx \; subject \quad to \qquad \sum_i^{\mathrm{n}} a_{ij}\, x_j +$$

$$\max_{\left\{S_i \cup \{t_i\} \mid S_i \subseteq J_i, |S_i| = [\Gamma_i], t_i \in J_i \setminus S_i\right\}} \left\{ \sum_{j \in S_i} \hat{a}_{ij} y_j + \left(\Gamma_i - [\Gamma_i]\right) \hat{a}_{it_i} y_t \right\} \le b_i, \qquad \forall i \tag{5}$$

$$-y_j \le x_j \le y_j, \qquad \forall j \in J_i$$

$$l \le X \le u, \quad y \ge 0$$

$$Maximize \qquad z = cx$$

$$subject \quad to \qquad \sum_j a_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \le b_i \quad \forall i$$

$$z_i + p_{ij} \ge \hat{a}_{ij}\; y_j \qquad \forall \mathrm{i, j}, \grave{o} J_i$$

$$-y_j \le x_j \le y_j \qquad \forall \mathrm{j} \tag{6}$$

$$l_j \le x_j \le u_j \qquad \forall \mathrm{j}$$

$$\left(p_{ij}, y_j, z_i\right) \ge 0 \qquad \forall \mathrm{i, j}, \grave{o} J_i$$

Where z, f and p are non-negative additional variables and ε is a given uncertainty level in the model. In model 7, which is a linear form of optimization, $n + k + 1$ variables and $m + k + n$ constraints are existed. The degree of confidence in the model against uncertainty depends on the parameters Γ_i. If

$\Gamma_i = 0$, the maximization statement is eliminated and the constraint condition is changed from uncertainty to certainty. If $\Gamma_i = |j_i|$ the degree of system protection against uncertainty is maximized and fully implemented. There are different values for Γ_i and it depends on the probability level of the deviation of *i*th constraint (p_i) and the number of uncertain parameters (n). Eq. (7) shows this dependence (Bertsimas et al., 2010).

$$\Gamma_j = 1 + \Phi^{-1}\left(1 - p_i\right)\sqrt{n} \qquad (7)$$

Where Φ is cumulative distribution of the standard Gaussian variable and n is uncertainty resources in each constraint.

2.4 Application of RMOLFP Method to Optimal Sustainable Cropping Pattern

2.4.1 Objective Function

In order to optimize the cropping pattern and align this model with the relative objectives, the objective functions in the present study are defined as Eq. (8):

$$Min: \varphi_{1-3} = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R} Fer_{tjsr} A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R} A_{jsr}} \qquad t = 1,2,3; \qquad (8)$$

The objective function ϕ_1 to ϕ_3 are related to the sustainable use of nitrogen (N), phosphate (P) and potash (K) fertilizers. In these functions, A_{jsr} represents the cultivation area crop *j* in season s for region *r*, and Fer_{tjs} represents the required amount of fertilizer by type *t* (N, P or K) to cultivate each hectare of crop *j* in season s for region *r*.

Functions ϕ_4 to ϕ_6 are related to sustainability to herbicides, fungicides and insecticides.

$$Min: \varphi_{4-6} = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R} Pes_{zjsr} A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R} A_{jsr}} \qquad z = 1,2,3 \qquad (9)$$

In these equations, Pes_{zjs} represents the required amount of pesticide by the type *z* per hectare of product *j* in season s for the region *r*.

Water resource productivity is another ecological objective of the optimal cropping pattern model that has been addressed in the objective function ϕ_7.

$$Min:\varphi_7 = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}\frac{NetW_{jsr}}{Eff_r}A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}A_{jsr}} \tag{10}$$

$NetW_{jsr}$ is the net water requirement for crop *j* in season *s* and region *r* (m^3 / ha), and Eff_r is irrigation efficiency in the region *r*.

The ecological dimension of sustainability of crop production in the proposed model is provided by objective functions ϕ_1 to ϕ_7.

The objective function ϕ_8 ensures the economic dimension of the sustainability of agricultural production (Eq. 11).

$$Max:\varphi_8 = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}\left(Mp_{jr}+Sp_{jr}-Cp_{jr}\right)A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}A_{jsr}} \tag{11}$$

In this equation, Mp_{jr}, Sp_{jr} and Cp_{jr} are the main crops value, the sub-crop value and the production cost for cultivating one hectare of crop *j* in region *r*, respectively.

It should be noted that the result of $Mp_{jr}+Sp_{jr}-Cp_{jr}$ is equal to the gross margin of crop *j* in region *r* ($/ha) and from now on, it will be shown with the symbol GM_{jr}.

The social dimension of a sustainable cropping pattern model can be considered in workforce recruitment for the agricultural labor force. In this regard, the objective function ϕ_9 (Eq. 12) tries to increase the workforce recruitment in the optimal cropping pattern.

$$Max:\varphi_9 = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}Lab_{jsr}A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}A_{jsr}} \tag{12}$$

Where Lab_{jsr} represents the amount of required labor to cultivate each hectare of crop *j* in season s and region *r* (man-day / ha).

2.4.2 Constraint sets

The scarcity of production inputs limits crop cultivation. Equations 13 to 19 clearly define these limitations. The set of irrigation water constraint is related to the amount of available water. Eq. (13) determines the allowable limit for the amount of water available for each area.

$$\sum_{j=1}^{J} \frac{NetW_{jsr}}{Eff_r} A_{jsr} \le TW_{sr} \qquad \forall s,r \tag{13}$$

TW_{sr} is the total amount of available water in season s and region r (m3).

The set of constraints (14) to (17) are related to the allowable limit for the amount of labor, agricultural machinery, fertilizer and pesticide, respectively.

$$\sum_{j=1}^{J} Lab_{jsr} A_{jsr} \le TLab_{sr} \qquad \forall s,r \tag{14}$$

$$\sum_{j=1}^{J} Mec_{jsr} A_{jsr} \le TMec_{sr} \qquad \forall s,r \tag{15}$$

$$\sum_{j=1}^{J} Fer_{tjsr} A_{jsr} \le TFer_{tsr} \qquad \forall t,s,r \tag{16}$$

$$\sum_{j=1}^{J} Pes_{zjsr} A_{jsr} \le TPes_{zsr} \qquad \forall \mathrm{z,s,r} \tag{17}$$

Where, $TLab_{sr}$, $TMec_{sr}$, $TFer_{tsr}$ and $TPes_{zsr}$, represents the total amount of available labor (man-day), available agricultural machinery (hour), Total available fertilizer of type t (kg) and amount of available pesticide of type z (kg or liter), respectively.

Eq. (18) relates to land and in this set, the cultivation area of crops is limited by the amount of available land in each region.

$$\sum_{j=1}^{J} \sum_{s=1}^{S} Sch_{jsr} A_{jsr} \le TA_r \qquad \forall r \tag{18}$$

The TA_r represents the amount of available land in the region r (ha) for all crops and Sch_{jsr} indicates the land occupancy coefficient. If the crops are cultivated each month (from planting to harvesting), the land occupancy coefficient of that crop in those months is one, and otherwise zero.

In order to rely on the optimal solutions and to accept the model presented in this study, the current profit of crop cultivation in each region should be provided (Eq. 19).

$$\sum_{j=1}^{J} \sum_{s=1}^{S} GM_{jr} A_{jsr} \ge Cur\,\mathrm{Pr}\,ofit_r \qquad \forall r \tag{19}$$

In this equation $CurProfit_r$ is the current profit in the region r.

The set of constraints 20 and 21 specifies the maximum and minimum production of agricultural products, respectively.

$$\sum_{s=1}^{S} Yield_{jr} A_{jsr} \le MaxProd_{jr} \qquad \forall jr \tag{20}$$

$$\sum_{s=1}^{S} Yield_{jr} A_{jsr} \ge MinProd_{jr} \qquad \forall jr \tag{21}$$

Where $Yield_{jr}$ is the yield of crop *j* in the region *r* and $MaxProd_{jr}$ and $MinProd_{jr}$ are the maximum and minimum allowable amount of production of agricultural products, respectively. The amount of maximum production in Eq. (20) is determined based on the potential of each region and macroeconomic considerations. The amount of minimum production in Eq. (21) is calculated based on self-consumption needs and food security policies set by the government for each region.

2.4.3 Uncertain data

There are many uncertain parameters in an optimization model for cropping pattern. In this study, the total amount of available water (TW_{sr}) and the gross margin (GM_{jr}) are considered as uncertain parameters. Therefore, by defining the parameter Γ_{sr}^{TW}, variables z_{sr}^{TW} and p_{sr}^{TW} and using model 6, the constraint of the total amount of available water (Eq. 13) is converted into two Eqs. 22 and 23.

$$E\sum_{j=1}^{J}\frac{NetW_{jsr}}{Eff_r}A_{jsr} + z_{sr}^{TW}\Gamma TW_{sr} + pTW_{sr} \le T\overset{n}{W}_{sr} \quad \forall \mathrm{s,r} \tag{22}$$

$$zTW_{sr} + pTW_{sr} \ge \varepsilon T\overset{n}{W}_{sr} \quad \forall \mathrm{s,r} \tag{23}$$

Where $T\bar{W}_{sr}$ represents the nominal value of the total amount of available water.

Considering GM_{jr} as an uncertain parameter, the two Eqs. 11 and 19 change. These equations, like Eqs. (22) and (23), are converted to robust form by defining new parameters and variables. Eq. (24) and (25) are formulated to robustification the objective function φ_8 (maximizing gross margin) and Eq. (26) and (27) are formulated to robustification the Eq. 19.

$$\varphi_8 = \frac{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}\left(G\bar{M}_{jr}\right)A_{jsr}}{\sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{r=1}^{R}A_{jsr}} - z^{GM1}\Gamma^{GM1} - \sum_{j=1}^{J}\sum_{r=1}^{R}p_{jr}^{GM1} \tag{24}$$

$$z^{GM1} + p_{jr}^{GM1} \ge \varepsilon G\overset{n}{M}_{jr} \quad \forall j,\mathrm{r} \tag{25}$$

$$\sum_{j=1}^{J}\sum_{s=1}^{S}GM_{jr}A_{jsr} - z^{GM2}\Gamma^{GM2} - \sum_{j=1}^{J}p_{jr}^{GM2} \ge CurProfit_r \quad \forall r \tag{26}$$

$$z^{GM2} + p_{jr}^{GM2} \ge \varepsilon G\bar{M}_{jr} \quad \forall j,r \tag{27}$$

2.4.4 Model evaluation

Monte Carlo simulation method is used to evaluate the proposed model (Figure 3). For this purpose, after solving the robust multi-objective linear fractional programming, 10,000 random numbers with specified distribution for the uncertain parameters (in this study, the amount of available water and gross margin) are generated. After solving the proposed mathematical programming model, the values of the optimal cultivation area (A^*_{jsr}) and generated numbers are replaced in Eq. 13 and 19. If the equations were not correct after these replacements, they are recorded as infeasible solution indicating model's inability to apply uncertain data.

This process is performed at different levels of probability deviation of constraint (p) and given uncertainty level (ε).

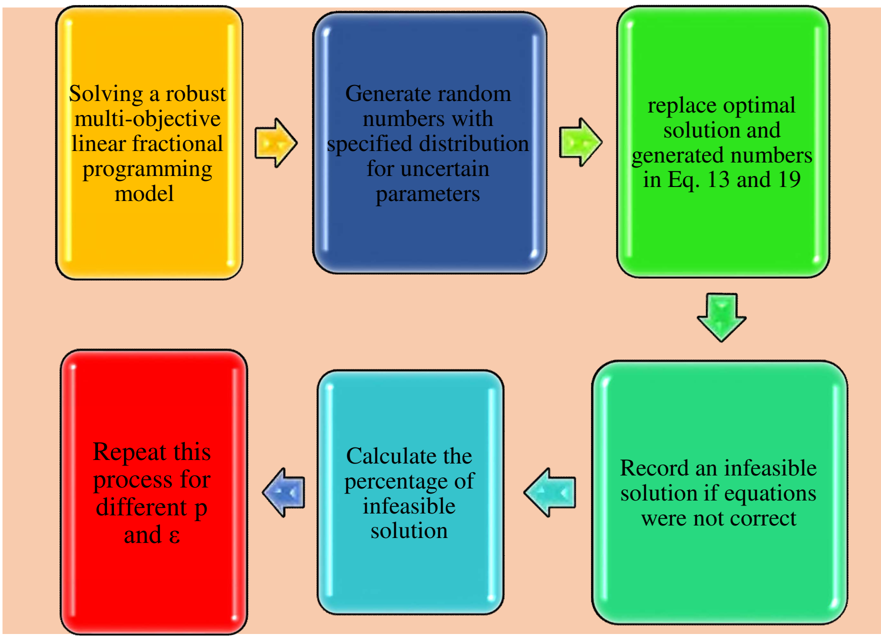

Figure 3. Monte Carlo simulation process to evaluate the capability of a robust multi-objective linear fractional programming model

3. Results

3.1 Primary data processing

In this study, all the required data were obtained from various governmental agencies such as the Jihad-e-Keshavarzi organization (Anonymous, 2018), Khuzestan Water and Power Authority and the Great Karoun Irrigation Network Operating Company (Anonymous, 2017) in the year 2017. In this network, there are generally winter and summer agricultural products in which 12 types of crops are cultivated. Some of these crops are perennial (such as alfalfa). Table 1 lists these crops along with the current cultivation area. Wheat is one of the most popular crops among farmers in this irrigation and drainage network due to its guaranteed price and elimination of income risk, with about 17,000 hectares cultivation area. Although the availability of water and canal length in the Aghili area is less than the Dimech area, the presence of more modern irrigation equipment in the Aghili area has made its current cultivation area (about 2800 hectares) the same as the area of Dimcheh.

Table 1. Crop cultivation area in the Gotvand irrigated and drainage network by operation zones (ha)

Crop	Gotvand	Aghili	Dimcheh	total	The share of the cultivation area (Percent)
Corn	0	1015	75	1090	3.19
Eggplant	212	251	1088	1551	4.54
Rice	736	1977	1902	4615	13.52
Beans	859	0	881	1740	5.1
Okra	0	580	293	873	2.56
Barley	32	61	90	183	0.54
Onion	10	110	0	120	0.35
Wheat	4468	6695	5782	16945	49.63
Canola	0	428	360	788	2.31
Vegetables	967	0	1837	2804	8.21
Broad bean	943	0	1015	1958	5.73
Alfalfa	631	119	725	1475	4.32
Total	8858	11238	14048	34144	100

Table (2) summarizes the important parameters used in the proposed model. Table (1) and Table (2) provide exciting findings on the relationship between the cultivation area and input consumption. Although the Corn cultivation area is lower than wheat and rice, the gross margin for corn ($ 5864 per hectare) is more than the mentioned crops (Table 1). The government has led a restriction on corn cultivation in the study area since the consumption of fertilizer and pesticide for its cultivation is more the other two crops. However, this coercion was accompanied by fierce opposition from farmers (due to poverty) and led to severe tensions between government bodies and farmers. It is also evident that despite the low consumption of these inputs in barley, the cultivation area of this crop is just about 183 hectares. The simplest reason is the low gross profit of this product ($ 192 per hectare) compared to other products, so the low gross margin has led to farmers' unwillingness to cultivate this crop.

Tables (1) and (2) show that the study area desperately needs a revision of the current cropping pattern. This change should be made in light of the problems already mentioned. Firstly, the farmers tend to participate in this change, and it is related to how much income, they can earn (more or equal than their current income) and secondly, due to the critical conditions of fertilizers and chemical pesticides consumption in the area, their consumption is drastically reduced. In other words, it is necessary to make a compromise between the different objectives in the area.

Table 2- Average technical and economic coefficients of agricultural product in the Gotvand irrigation and drainage network (per hectare)

	Rice	Corn	Beans	Broad bean	Alfalfa	Onion	Barley	Wheat	Canola	Okra	Vegetables	Eggplant
Gross margin ($)	1842	5864	100	401	1106	1003	192	412	214	2904	3481	2958
Production Cost ($)	1603	1378	1031	817	2146	1910	563	768	740	1824	1620	954
Phosphate (kg)	239	109	112	60	238	114	22	98	88	55	124	36
Nitrogen (kg)	395	472	224	30	16	248	123	353	279	324	367	152
Potash (kg)	0	14	0	60	17	9	0	6	25	46	53	17
Total fertilizer (kg)	634	595	336	150	272	370	146	457	393	344	444	371
Herbicide (kg)	0.88	3.07	0	0	0.19	1.86	0.28	1.48	3.08	1.18	1.44	1.8
Insecticides (kg)	1.52	0.58	0	0	0.14	1.68	0.01	0.12	0.76	0.7	0	1.6
Fungicides (kg)	0	0	0	0	0.06	1.24	0.01	0.01	0.14	0	0.11	0.12
Total pesticide(kg)	2.4	3.65	0	0	0.4	4.78	0.3	1.61	3.98	1.2	0	3.24
Net water requirement(m^3)	10260	3084	6252	5868	14448	5052	2148	2724	4106	13973	9502	4523
Machinery (hours)	25	31	34	40	38	24	28	26	36	28	24	40
Labor (man-day)	121	15	31	32	60	43	8	7	8	85	24	16

3.2 Software and model solving algorithm

The proposed mathematical algorithms are modeled by a robust multi-objective fractional linear programming method and are fully coded in GAMS optimization software and solved for different levels of p and ε and generate different scenarios to apply conservatism against uncertainty. The optimization method chosen for solving this model was CONOPT4, which is an optimizer for solving large-scale nonlinear programming problems. CONOPT4 is based on the Generalized Reduced Gradient (GRG) method and is developed in GAMS software by the Danish Consulting and development firm ARKI (GAMS/CONOPT4, 2015).

3.3 Results of the RMOLFP Model Solution

3.3.1 Cultivation area

With the implementation of this model, a massive difference in the current and proposed patterns was observed. Referring to Table (3), the details of these changes are identified, and the crop cultivation level is presented at p = 1 and 0 (scenario 1), which in fact, models the certainty conditions. Also, the model results at p = 0.1 and ε = 0.1 (scenario 2) are presented for applying the uncertainty conditions, which creates an excellent opportunity for comparing these two scenarios.

Table (3)reports the area of each crop for cultivation under two scenarios. It is observed that onion in both scenarios was excluded from the model. This can be traced to the large consumption of inputs and the low gross margin for this product. For example, the total pesticide use (herbicides, insecticides and fungicides) for this product was 4.78 liters per hectare, which is more than the other crops. However, the share of this product is insignificant, and its overall elimination due to regional conditions seems reasonable. Due to the significant share of wheat and rice in the current cropping pattern (about 63%), the cultivation area variation of both crops in two scenarios is analyzed.

Table (3) shows that there is an increase (in scenario 1) in the cultivation area of wheat and rice, which increases the cultivation area to 2635 hectares in the entire area. With the increase in model protection against uncertainty, the proposed cultivation area has decreased significantly. The main reason for this reduction compared to scenario 1 is the extensive water use of these two products. This result seems reasonable due to the increased conservatism leading to a decrease in the amount of available water.

The cultivation area of some crops such as rice and corn have been increased in the proposed models to offset the reduction in profits in both scenarios. So, the policy that is currently being implemented by the government to limit corn cultivation area is not appropriate. This policy increases the dissatisfaction of farmers and, on the other hand, loses the alternatives. For example, the government could authorize the cultivation of corn along with barley, which has an increased cultivation area on both scenarios, which will increase farmers' interest in cultivating barley (Table 2). However, this policy should be done with caution if the whole proposed pattern is implemented .

It can be observed that by increasing the model's protection against uncertainty (decreasing the probability level p), the total cultivation area decreases; at $p = 1$, the cultivation area increased by 9.34%, and at $p = 0.1$ the mentioned area decreased by 3.63%.

Table 3. Cultivation area of optimal cropping pattern of Gotvand irrigation and drainage network at different levels of p and ε

Region	Rice	Corn	Beans	Broad bean	Alfalfa	Onion	Barley	Wheat	Canola	Okra	Vegetables	Eggplant	Total
(Scenario 1)													
Gotvand	1128	0	403	852	879	0	65	4849	0	0	1605	76	9857
Aghili	2731	1446	0	0	229	0	0	6897	95	1090	0	350	12838
Dimcheh	2610	424	273	1021	635	0	329	5970	112	286	2627	678	14965
Total	6469	1870	676	1873	1743	0	394	17716	207	1376	4232	1104	37660
Percentage change	28.66	41.72	-157.3	-4.53	15.38	-100	53.55	4.35	-280.6	36.54	33.74	-40.47	9.34
(Scenario 2)													
Gotvand	1128	0	403	852	879	0	65	4849	0	0	1605	76	9857
Aghili	2270	1446	0	0	119	0	0	6816	95	1049	0	350	12145
Dimcheh	2045	424	273	922	232	0	329	4217	112	91	1905	393	10943
Total	5442	1870	676	1774	1229	0	394	15883	207	1139	3510	819	32943
Percentage change	15.2	41.72	-157.3	-10.36	-19.97	-100	53.55	-6.69	-280.6	23.38	20.12	-89.28	-3.63

3.3.2 Consumption of chemical inputs (ecological dimension)

Table (4) presents the results of the changes in fertilizer and pesticide in the study area. However, the absolute reduction in the number of consumed inputs in optimal models does not necessarily indicate an improvement in the use of these production resources, and it just happened by reducing the cultivation area. Therefore, the average fertilizer application per hectare can be a good criterion for examining the effect of cropping pattern change on the optimal use of these resources. The results show that the fertilizers and pesticides used has decreased by approximately 6% and 8%, respectively, in both scenarios. Due to the current challenging economic situations in Iran (Poor economic growth, sanctions and unemployment), reducing this amount of fertilizer is crucial for the agriculture sector.

Table 4. Average current and optimal consumption of pesticides and Fertilizers in the Gotvand Irrigation and Drainage Network (Unit: Kg or L/ha)

Model	Region	Phosphate	Nitrogen	Potash	Total fertilizer	Herbicide	insecticide	Fungicides	Total pesticides
Current	Gotvand	129.9	309.5	18.5	457.9	1.14	0.26	0.02	1.43
	Aghili	136.8	402.8	10	549.6	1.76	0.58	0.03	2.36
	Dimcheh	131.4	322.1	19.4	472.8	1.31	0.47	0.03	1.81
	Total	132.7	344.8	15.9	493.4	1.4	0.43	0.03	1.86
Scenario 1	Gotvand	127.2	293.8	18.4	439.3	1.1	0.26	0.02	1.38
	Aghili	126.3	360.8	9.7	496.8	1.5	0.56	0.01	2.08
	Dimcheh	125.7	312.2	18.7	456.6	1.22	0.43	0.03	1.68
	Total	126.4	322.3	15.6	464.3	1.27	0.42	0.02	1.71
	Percentage change	-4.8	-6.5	-2.1	-5.9	-9	-4.13	-29.63	-8.19
Scenario 2	Gotvand	127.2	293.8	18.4	439.3	1.1	0.26	0.02	1.38
	Aghili	121.5	362.8	9.9	494.1	1.54	0.53	0.01	2.09
	Dimcheh	124.4	315.2	18.7	458.4	1.22	0.43	0.03	1.67
	Total	124.4	323.9	15.7	464	1.29	0.41	0.02	1.71
	Percentage change	-6.3	-6.1	-1.7	-6	-8.17	-6.43	-32.09	-8.15

3.3.3 System profit (economic dimension)

The vital point in examining the proposed model is that with increasing system protection against uncertainty (decreasing level of p from 1 to 0.1), the Total profit has increased. Figure 4 is presented to investigate this issue better and analyze its sensitivity at different levels of p ranging from 0.1 to 1 with steps 0.1 for each region. It is observed that as the level of p increases, the amount of total profit decreased in all three regions. In other words, there is a trade-off correlation between the degree of system protection against uncertainty (robustness) and the amount of total profit.

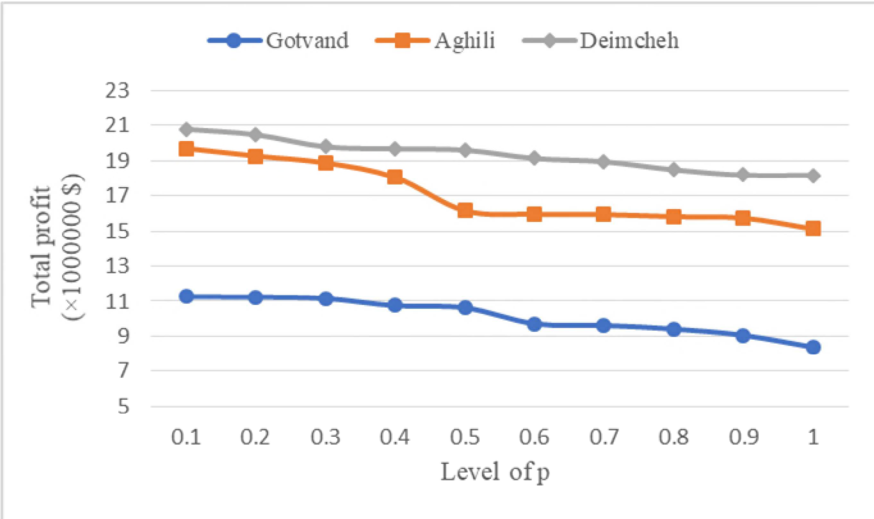

Figure 4.Total profit at different levels of p in the Gotvand irrigation and drainage network regions

3.3.4 Other inputs (social and ecological dimensions)

Table (5) reports the utilization of other inputs generated by implementing the two scenarios of optimal cropping patterns and the current situation. In both scenarios and all three regions, irrigation water use per hectare decreased. In the Gotvand region, the reduction of water use per hectare is increased with increasing system protection against uncertainty, and in other regions, it remains unchanged. In other words, there is no particular trend (such as total profit) for water consumption by increasing the system protection against uncertainty. In Gotvand and Dimcheh regions, as the level of p decreases, the utilization of labour and machinery does not have a significant change, while in the Agheli region, by decreasing the level of p, the increase in the labour is about 10% lower than the first scenario.

Table 5. Average, current and optimal consumption of other agricultural inputs per hectare in different scenarios

			Scenario 1		Scenario 2	
		Current amount	Optimal amount	Percentage Change	Optimal amount	Percentage Change
Gotvand	Irrigation water (Cubic meters)	6403.7	5804.8	-9.4	5804.8	-36.9
	Machinery (hour)	32.1	28.3	-11.8	28.3	-11.8
	Labor (man-day)	30.1	30.8	2.2	30.8	2.2
Aghili	Irrigation water (Cubic meters)	6040.4	5519.8	-8.6	5284.6	-7.4
	Machinery (hour)	27.2	27.2	0	27.2	0
	Labor (man-day)	33	40	21.2	36.8	11.6
Dimcheh	Irrigation water (Cubic meters)	6598.7	6138.9	-9.1	5997.5	-9.1
	Machinery (hour)	32.1	28	-12.6	28	-12.8
	Labor (man-day)	36.4	36.4	0	36.4	0

3.4 Evaluation the capability of the proposed model against uncertainty

Monte Carlo simulation method was used to validate the proposed model, as shown in Figure 3. In this regard, 10,000 random data were generated for the available water parameter with uniform (at a given distance) and normal (with 95% convergence) distributions for uncertain parameters GM_{jr} and TW_{sr}. Then, the feasibility of randomly generated numbers was investigated by using the simulation method. Figures (5) and (6) show the results of this simulation method for different levels of p and ε for random numbers generated using uniform and normal distributions, respectively. It is observed that in both distributions, with the decrease in the level of p, the percentage of infeasibility is reduced; So that at the 10% given uncertainty level (ε=0.1) with a uniform distribution, with the decrease level of p from 100% to 10%, the infeasibility percentage is decreased from 56% to 17%. It is also found that by increasing the given uncertainty level in both distributions, the average infeasibility is decreased. The lower infeasibility at high levels of conservatism (lower levels of p) indicates the considerable robustness of the proposed optimal cropping pattern model to overcome the uncertainty.

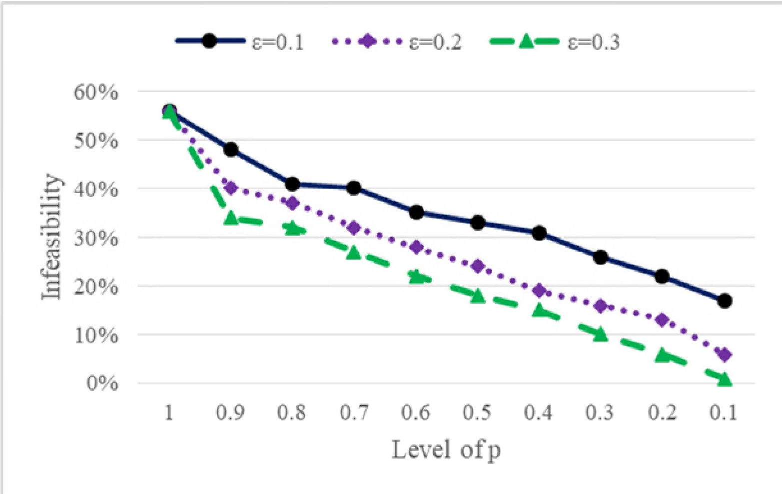

Figure 4. Infeasibility percentage of the proposed model assuming uniform distribution over a given interval

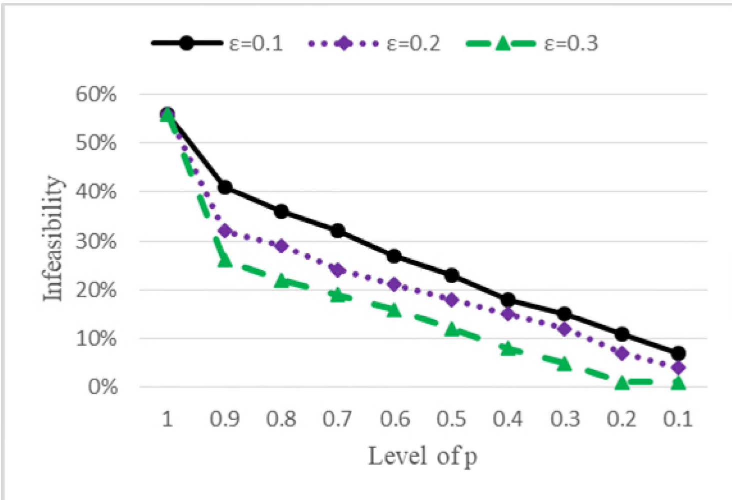

Figure 5. Infeasibility percentage of the proposed model assuming normal distribution with 95% convergence

4. Discussion

In this section, the results of the present study and previous studies are compared based on three ecological, economic and social dimensions of the optimal sustainable cropping pattern. A summary of this discussion is provided as follows:

4.1 Ecological dimension

Increasing the cultivation area in the Gotvand irrigation and drainage network led to a decrease in the total area under the proposed model, improperly. Reducing the cultivation area in optimal cropping pattern models is not limited to this study and has been recommended in most similar studies for different regions of Iran (M. S. Sabouhi & Mardani, 2013). For example, Mardani Najafabadi et al. (2019), used the multi-objective robust optimization method in their cropping pattern programming model and they found that about 16.5% of the total cultivation area in Isfahan province has been reduced.

According to statistics published by the Khuzestan Agricultural Jihad Organization, the use of fertilizers and pesticides in the Gotvand irrigation and drainage network has an upward trend and the consumption of these two destructive inputs will almost double. It is crucial to prevent the increase in the use of fertilizers and pesticides for this region, however, the reduction in their use in the proposed model is less than 10% (Anonymous, 2017).

In contrast, Neamatollahi, Vafabakhshi, Jahansuz, and Sharifzadeh (2017) applied different scenarios by using a fuzzy multi-objective planning model, they found that the reduction rate of fertilizer and chemical pesticide consumption are 38% and 35%, respectively. These percentages are realized only when the demand for the industrial and livestock sectors is not taken into account. If this demand is calculated, the consumption of fertilizers and pesticides will increase sharply by 52 and 11 percent, respectively. The important point in the present study is that the need for self-consumption and food safety considerations are considered in Equation 21 and this has led to more input consumption of fertilizers and pesticides. However, contrary to the study of Neamatollahi et al. (2017), the consumption of these two destructive inputs has decreased.

In many studies that have tried to optimize the cropping pattern, the ecological dimension has been considered only for the optimal use of irrigation water (C. Zhang et al., 2018; F. Zhang et al., 2018). Tan and Zhang (2018) optimized irrigation water use efficiency using robust fraction programming. The result of their study is that with increasing conservatism (reducing the level of probability of deviation), the efficiency of water consumption decreases.

4.2 Economic dimension

It should be noted that the economic and ecological dimensions are closely related. For example, in most studies that consider environmental objectives, optimal use of inputs that lead to disruption of the ecological system has been suggested as a viable solution for economic (lower cost on the consumption of production inputs) and ecological (optimal use of chemical inputs) sustainability (Mardani Najafabadi et al., 2019).

Sensitivity analysis of gross profit in the present study showed that with increasing system protection against uncertainty, system profit decreases. According to a review of research, this sensitivity analysis has been used in studies such as Tan & Zhang (2018) and M. S. Sabouhi and Mardani (2013) that used a robust optimization approach. Depending on the number of uncertain parameters in the models, this decrease in profit or increase in cost is distinctive.

Increasing the protection of the system against uncertainty is not limited to the robust optimization method. For example, in the study of Zhang et al. (2017), the probability of occurrence for different inflow is considered as different levels of conservatism. The profit of the system has increased by increasing the conservatism which means the protection of the system against uncertainty is reduced. Wang et al. (2019) used a bi-level multi-objective linear fractional programming model with the theory of fuzzy sets and different levels of alpha (Uncertainty condition) to redistribute water to the agricultural, industrial, urban, and ecological sectors of the Heihe River basin in China. They found that increasing the level of conservatism (alpha levels) reduced the total gross profit, especially in the agricultural sector.

Filippi et al., (2017) used the mixed integer linear programming model in similar conditions. The objective function of their model was different, so they maximized the net return function with the approach of Conditional Value-at-Risk as a safety measure. Increasing the risk-aversion parameter in this model, which can be considered as increasing the protection of the system against uncertainty, led to a decrease in profit.

4.3 Social dimension

In the present study increasing employment and food security has been considered as two aspects of social dimensions. According to the results, by implementing the cultivation pattern introduced in this study, the total employment rate will increase which shows the priority of ecological dimension in Gotvand region (especially reducing the use of fertilizers and pesticides). Although the aspect of food security in the present study is not considered as a main objective, however, in Equation 21, the need for self-consumption as well as government policies on food security when estimating the right-hand side of this constraint (the minimum production rate of each product) is calculated.

Mardni Najafabadi et al., (2019) considered Maximization of the use of labor (employment aspect) and minimization of the net import of energy from agricultural products (food security aspect). As the result, the employment rate in the whole region increased by 9%; But its relative rate (labor per hectare) has decreased by 11 percent. In this study, the food security index did not improve due to a 2% increase in net energy imports. Considering the increase in population and the consequent increase in the need for calories, this result seems reasonable. However Wineman and Crawford (2017) studied that due to the importance of the aspect of food security in a country, its only main objective is to maximize calorie production through the cultivation of agricultural products.

Increasing social equality is one of the important indicators in some studies of water or land redistribution pattern. Increase social equity in water redistribution with the aim of increasing the Gini coefficient in the equitable distribution of irrigation water is another economic dimension that studied by Wang et al. (2019). The results of this redistribution showed that if the proposed model is implemented, the Gini coefficient of water distribution is reduced, which indicates a reduction in the distribution inequality.

4.4 Summery

Due to many aspects of the optimal cropping pattern, Table 6 was designed to provide a summary of the status of the studies previously discussed. Although, it should be noticed that these studies have different objectives depending on the areas under study and the different priorities of each of them in solving the challenges, so considering the different challenges is not the reason for the superiority of the studies.

The proposed model in the present study does not apply only the supply-demand balance aspect since the transportation equations in this model is not provided. In the study of Mardani Najafabadi et al. (2019), agricultural products could be transferred from one county to another and also outside of Isfahan province. For this reason, the lack of supply of products from outside the province or other county was compensated. However, in this study, adding this feature required redesigning the model, which was not necessary due to regional priorities. As can be seen, this aspect has not been considered in most studies.

Table 6. Comparison of the results of the present study with others

			Economic dimension				Ecological dimension	Social dimension	
NO.	Title	Mathematical programming model	Optimal utilization of inputs	Gross profit increase	Supply- demand balance	Applying uncertainty condition	Environmental considerations	Employment	Food security
1	(Mardani Najafabadi et al., 2019)	Robust Multi-Objective Programming	✓	✓	✓	✓	✓	✓	✓
2	(C. Zhang et al., 2018)	inexact robust two-stage mixed-integer linear programming	✓	✓	✗	✓	✓	✗	✗
3	(Wineman & Crawford, 2017)	Liner programming	✓	✓	✗	✗	✗	✗	✓
4	(Zhang et al., 2017)	interval multistage joint-probabilistic chance constrained programming	✓	✓	✗	✓	✓	✗	✗
5	(Zeng, Kang, Li, Zhang, & Guo, 2010)	Fuzzy multi-objective linear programming	✓	✓	✗	✓	✓	✗	✗
6	(F. Zhang et al., 2018)	interval nonlinear multi-objective programming	✓	✓	✗	✓	✓	✗	✗
7	(Filippi et al., 2017)	Mixed integer linear programming	✓	✓	✗	✓	✗	✗	✗
8	(Tan & Zhang, 2018)	Robust fractional programming	✓	✓	✗	✓	✗	✗	✗
9	(Wang et al., 2019)	bi-level multi-objective linear fractional programming	✓	✓	✗	✓	✓	✗	✓

10	Proposed model	Robust Multi-Objective Fractional Linear Programming	✓	✓	✗	✓	✓	✓	✓

5. Conclusion

Over the past few decades, environmentalists have consistently emphasized the need to create a sustainable agricultural system because of imbalances between water supply and demand, falling aquifers, increasing fertilizer and pesticides use and depleting soil resources to conserve valuable environmental resources. Therefore, assessing the sustainability of farming systems to prevent the degradation of water and soil resources and reducing economic and social damages has become one of the top priorities of agricultural policymakers. Hence, this study aims to achieve an optimal cropping pattern for balancing the consumption of agricultural inputs (especially fertilizers and pesticides) by using a robust multi-objective fractional programming approach based on two scenarios (with and without uncertainty). The study area was located under the irrigation and drainage network of Gotvand in Khuzestan province, Iran, while it is dissimilar in terms of the average consumption of fertilizers and pesticides due to other provinces. The model was solved at different levels of deviation probability of each constraint (p) in two scenarios. The results showed that using the optimal cropping pattern in both scenarios made it possible to achieve the appropriate and optimal use of agricultural inputs (especially fertilizers and pesticides), which is the main objective of the study. However, the gross profit of the proposed model shows a slight increase in increasing system protection against uncertainty. Since, in the real world, the probability of uncertainty in the utilized data is higher, it is, therefore, advisable to use scenario (2) results to apply changes in the cropping pattern. Different and sometimes conflicting objectives in the structural programming scheme of the cropping pattern have been considered. It is possible to compromise between the considered objectives in the RMOLFP model, which is recommended to decision-makers. On the one hand, farmers are encouraged to implement the proposed model (due to the increase in gross profit) and on the other hand, the rate of water and chemical inputs (fertilizer and pesticides) consumption, which are in line with the implementation of the sustainable optimal cropping pattern, will be reduced.

6. Declarations

Availability of data and materials

All data generated or analyzed during this study are included in this published article.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Mostafa Mardani Najafabadi: Conceptualization, Methodology, Software, Formal analysis and investigations, Writing - Original Draft, Writing - Review & Editing, Resources.

Niloofar Ashktorab: Conceptualization, Methodology, Software, Formal analysis and investigations, Writing - Original Draft, Writing - Review & Editing, Resources.

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Figures

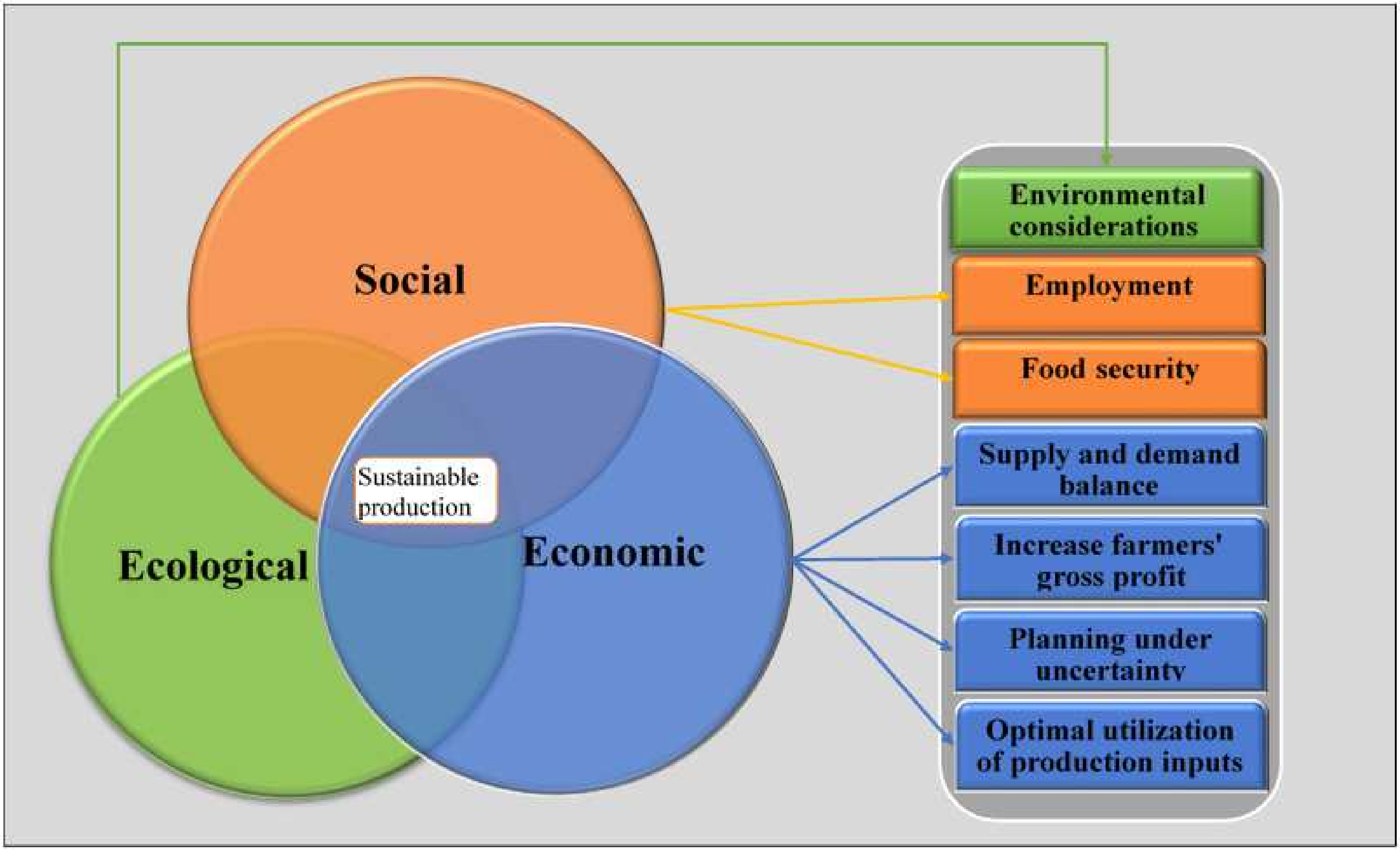

Figure 1

Tree dimensions of sustainable optimal cropping pattern

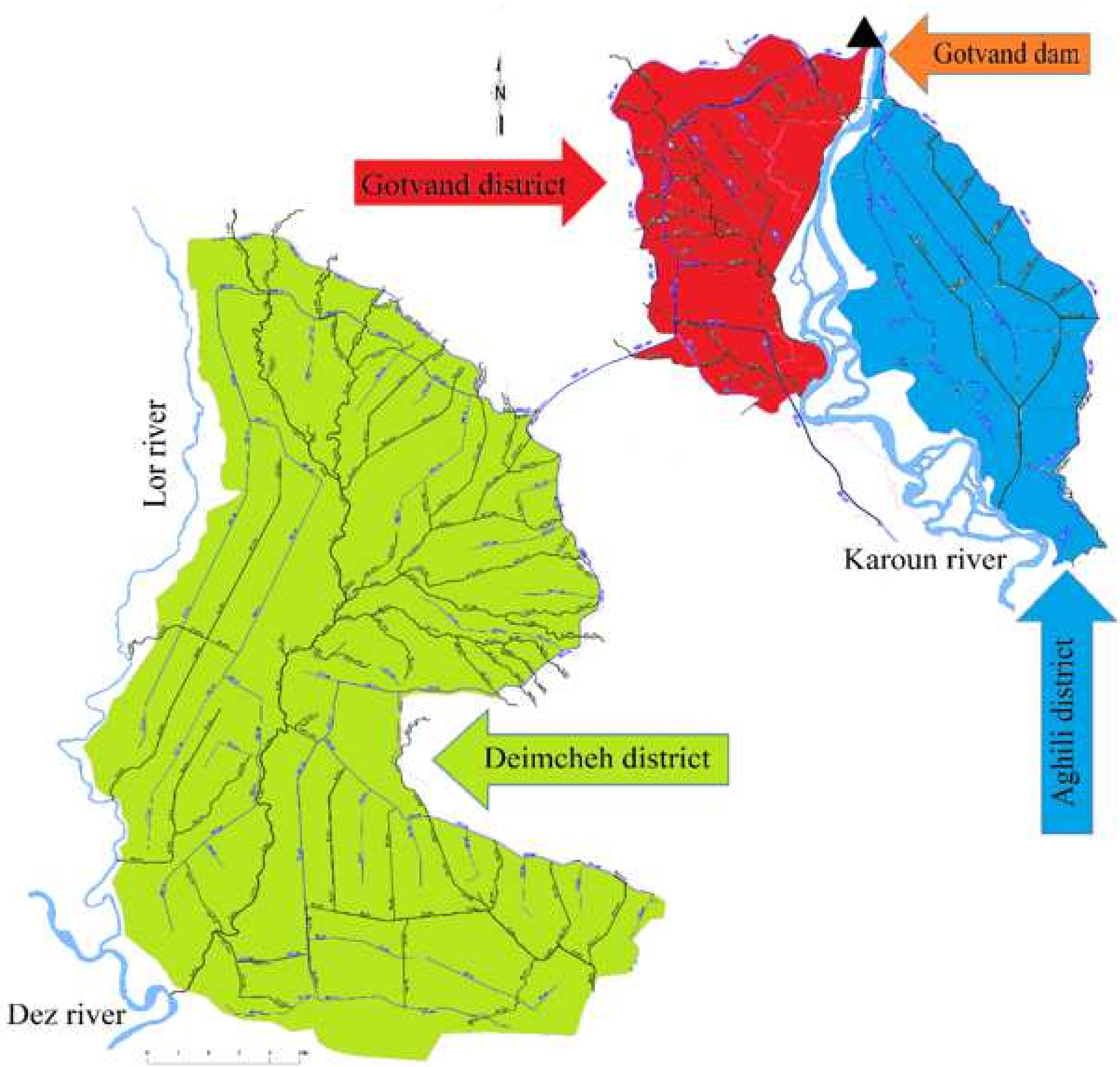

Figure 2

Schematic of the Gotvand irrigation and drainage network Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

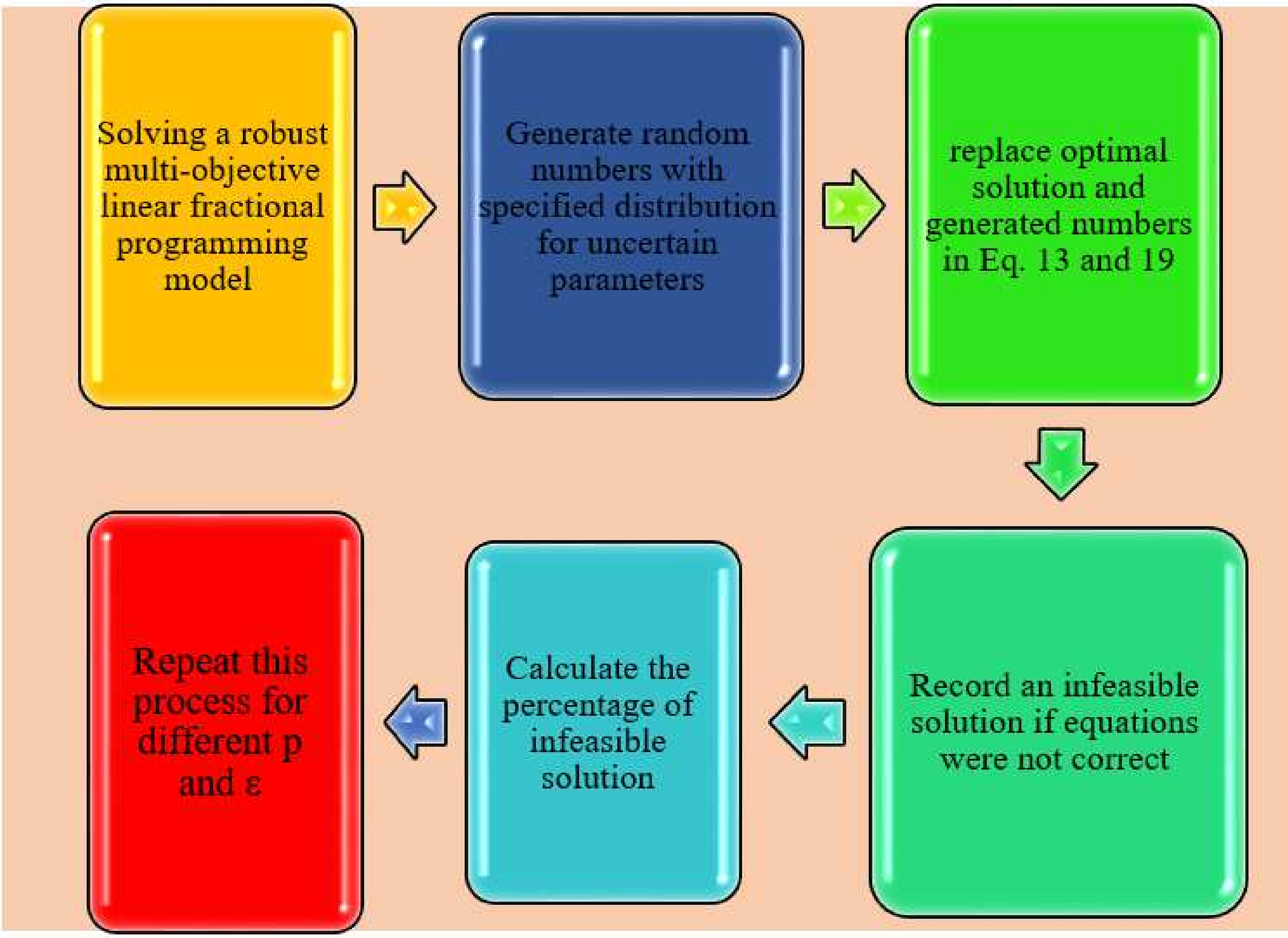

Figure 3

Monte Carlo simulation process to evaluate the capability of a robust multi-objective linear fractional programming model

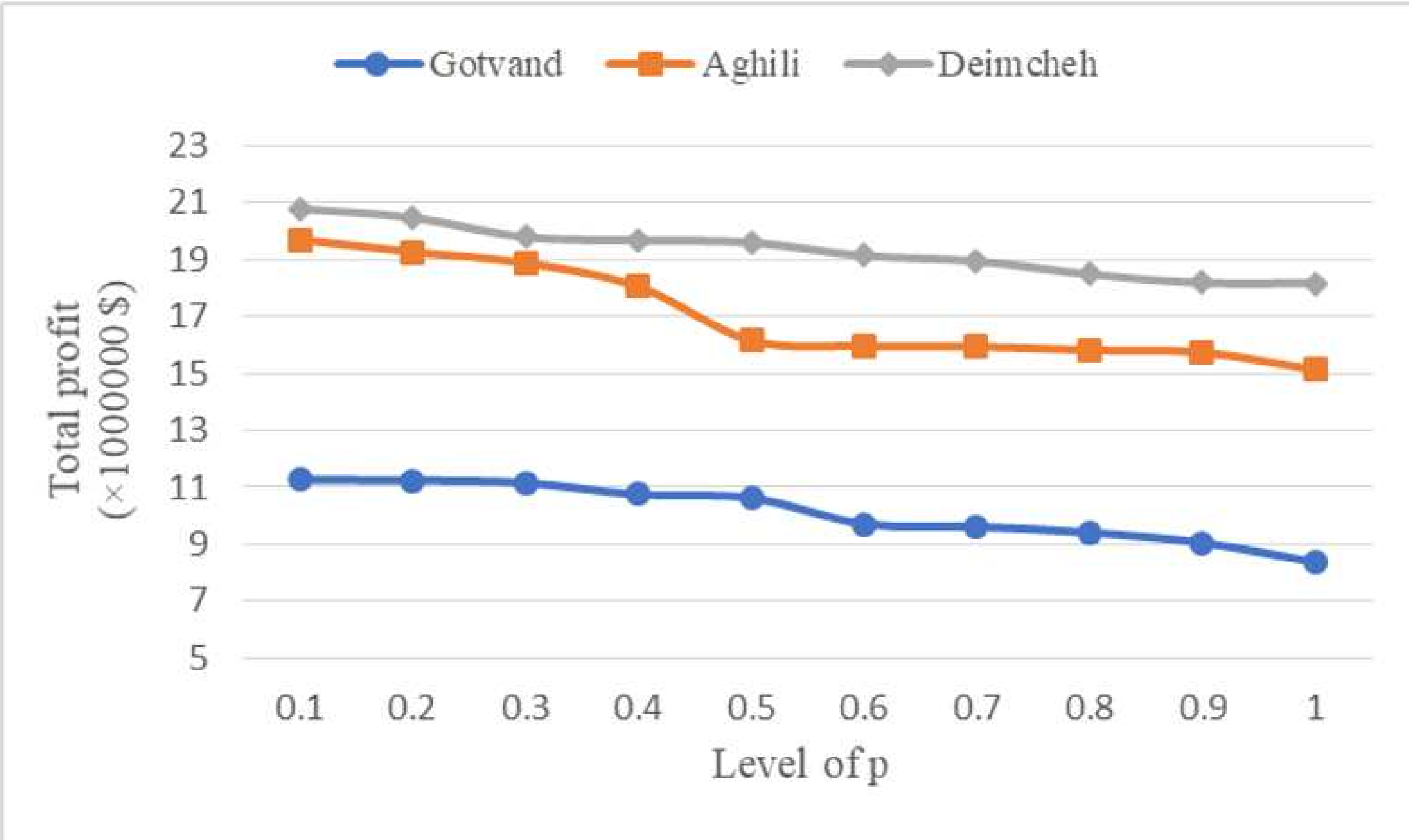

Figure 4

Total profit at different levels of p in the Gotvand irrigation and drainage network regions

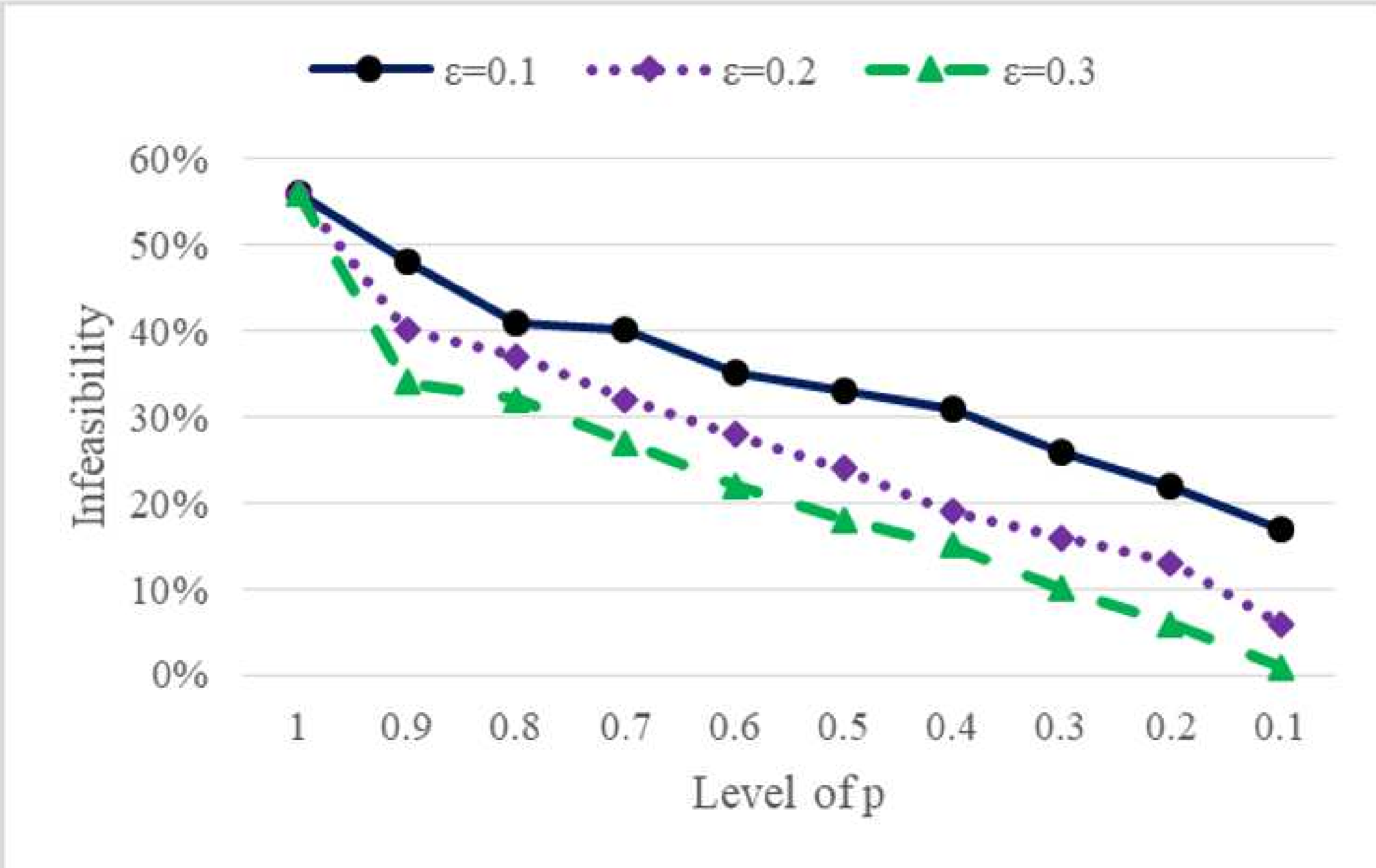

Figure 5

Infeasibility percentage of the proposed model assuming uniform distribution over a given interval

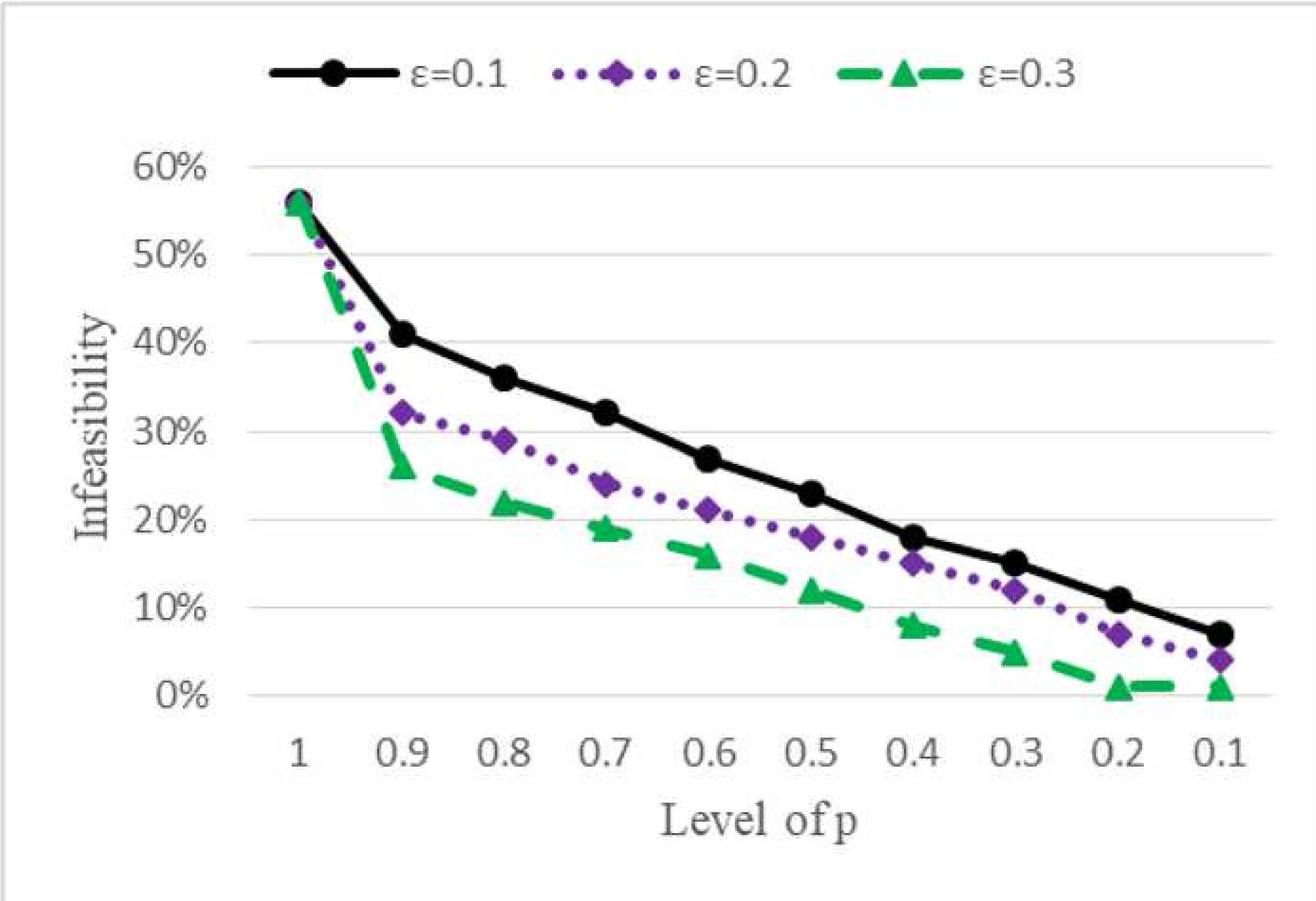

Figure 6

Infeasibility percentage of the proposed model assuming normal distribution with 95% convergence