International Journal of Agricultural Management and Development (IJAMAD)
Available online on: www.ijamad.iaurasht.ac.ir
ISSN: 2159-5852 (Print)
ISSN:2159-5860 (Online)

Optimal Cropping Pattern Modifications with the Aim of Environmental-Economic Decision Making Under Uncertainty

Mostafa Mardani [1*], Saman Ziaei [2] and Alireza Nikouei [3]

Received: 04 May 2016,
Accepted: 18 June 2018

Abstract

Sustainability in agriculture is determined by such aspects as economic, social, and environment. The multi-objective programming (MOP) model has been a widely used tool for studying and analyzing the sustainability of agricultural systems; however, optimization models, in most applications, have to use data that are uncertain. Recently, robust optimization has been used as an optimization model that incorporates uncertainty. This paper develops a framework for environmental-economic decision-making that considers the environmental and economic sustainability criteria in determining an optimal allocation of agricultural areas that cover an irrigation network under uncertain data. The primary uncertain parameter of the robust model was the quantity of available water for each season. The application of the proposed model to the case study of the right fringe of the Nekooabad irrigation network in the province of Isfahan, Iran demonstrates the reliability and flexibility of the model. The results show that the optimal total gross margin decreases with higher robustness levels. To compensate for the loss of gross margin of farmers in the robust pattern, efficiency enhancement policies were emphasized.

Keywords:
multi-objective programming, optimal cropping pattern, sustainability, uncertainty

[1] *Agricultural Sciences and Natural Resources University of Khuzestan*
[2] *Assistant Professor of Agricultural Economics, University of Zabol*
[3] *Assistant Professor of Economic, Social and Extension Research Department, Isfahan Agricultural and Natural Resources Research and Education Center, AREEO, Isfahan, Iran*
* *Corresponding author's email: m.mardani@ramin.ac.ir*

INTRODUCTION

The continuing debate on sustainability has raised grave concerns for the integration of environmental and economic aspects in developing a decision-making process. To make agricultural sustainability quantifiable, it is important to explain what it means. There are many confusing definitions of agricultural sustainability (Bell & Morse, 2008; Hansen, 1996). For example, it can be defined as the ability of agricultural systems to satisfy different demands as time change. Yet, it is valuable to point out that this description of sustainability has some problems that limit its empirical use in the real world. For example, we have to deal with the temporal nature of sustainability. In order to solve these difficulties, we can regard the concepts of sustainability as embodying three main dimensions: environmental, economic, and social (Yunlong & Smit, 1994).

Crop area planning is essential for agricultural sustainability, and it can decide how much input should be allocated to different cropped areas in order to accomplish certain goals under the limitations of available resources. The most prevailing policy to approach agricultural sustainability is to reduce or stop using chemicals, particularly fertilizers and pesticides. Accordingly, a sustainable optimal cropping pattern requires the consideration of multiple objectives, including environmental, economic, social, and other factors (Yu et al., 2013). In other words, as far as sustainability is concerned, we should compare levels of outputs or economic indicators with levels of contaminant inputs (Monteith, 1990).

Multi-criteria decision-making (MCDM) techniques are particularly helpful for environmental and economic analysis as well as decision-makers' viewpoints in the decision-making process. Various studies have already used MCDM techniques to approximate agricultural sustainability in making environmental-economic decisions (Chang et al., 2008; Diamond & Wright, 1989; Gibert et al., 1985; Morse et al., 2000; Seppelt & Voinov, 2003; Stewart et al., 2004). For instance, Hafkamp and Nijkamp (1986) used MCDM techniques (compromising programming (CP) techniques) for integrated economic-environmental-energy policy analysis. Ying-bin and Weimin (2016) linked a farmer crop selection model (FCS) with an agronomic model (EPIC) to simulate cropping pattern in Northeast China. Chen et al. (2010) applied multi-agent system (MAS) to study farmers' decision making and Yu et al. (2013) set up a CroPaDy model at village and town level to predict spatial patterns of crops. Eshraghi Samani and Poursaeed (2015) studied the comparative advantages of main agricultural products and its connection to cropping pattern in Ilam Province. Zekri and Romero (1993) used the MCDM approach to find the best compromising solution combining various dimensions of agricultural sustainability, such as net present value (NVP), employment, water consumption, and energy use. Gomez-Limon and Riesgo (2009) described a comparative analysis of alternative methods for constructing composite indicators to measure the sustainability of the agricultural sector to irrigated agriculture in the Duero basin in Spain. The three widely popular methods used to calculate the composite indicators of agricultural sustainability (CIAS) include Principal Components Analysis (PCA), analytical hierarchy process (AHP) and a Multi-Criteria technique (MCDM) based on the augmented Chebyshev distance function (Larimian et al., 2013). Tiwari et al. (1999) developed a framework for environmental-economic decision making that includes the environmental and economic sustainability criteria using Compromising Programming (CP) and Analytical Hierarchical Process (AHP) with a case of the Phitsanulok Irrigation Project (PIP) located in the Northern Plains of Thailand.

Most of the previous studies have not shown noticeable differences from expectation. This may rarely happen in real life, because most of the data can be imprecise or vague and as such contribute to error.

The main purpose of this study was to formulate a Multi-Objective Programming (MOP) model for assigning optimal allocation of agricultural areas on the right fringe of the Nekooabad irrigation network located in the province of Isfahan, Iran and then, to compare the existing crop patterns. compromising programming method was used to solve MOP. In this method, a set of objectives can be used to accomplish "best compromising" solution in the sense of the sustainable use of resources. A robust optimization counterpart proposed by Bertsimas and Sim (2004) was used to deal with the uncertainty of the available irrigation water parameter. This study tries to achieve composite indicators of agricultural Sustainability (CIAS) through maximizing economic (farmer's profit) and social factors (manpower use), and minimizing environmental pollution and the consumption of the available resources (fertilizers, pesticides, and agricultural irrigation water).

METHODOLOGY

Preliminaries of related models

Multi-objective programming (MOP) model

The generic MOP problem is as follows:

$$Eff\ z(x) = [Z_1(x), Z_2(x), \dots, Zq(x)] \tag{1}$$

where *Eff* means searching for the efficient solution (in a minimizing or maximizing sense) and F represents the feasible set.

There are three ways to generate the efficient set from Eq.1: the weighting, constraint, and multi-criterion simplex methods. Details of these methods can be found in Cohon (1978). To some extent, CP is a natural and a logical complement for MOP. MOP seeks to obtain the Pareto-efficient subset from the feasible solutions for a multi-objective problem. Yet, to determine that optimum solution, it is necessary to introduce the DM's preferences. CP finds it in a very realistic way, without concerning about the reliance on the questionable assumptions of the traditional utility theory (Romero & Rehman, 2003).

In CP, the ideal point or solution is defined as the best score on each criterion within a given set of criteria which serves as a reference point, because, in reality, it is almost impossible to have an ideal solution. In this context, the best alternative is the closest one to the ideal point. This closeness to the ideal point is determined by a family of standardized LP matrices and is mathematically expressed as:

(2)

where

(3)

$L_p\ (S_j)$ is the distance matrix, which is a function of the decision alternative S_j, and the parameter p (The scaling coefficient); μ_j is the weights representing the importance of the discrepancy between the jth objective and the ideal point. In other words, μ_j measures the relative importance of the *j*th objective in a given decision situation. Z^*j is the ideal or the best value for the *j*th objective; and Z_*j is the anti-ideal or nadir point for the *j*th objective.

The family of distance functions (Eq.2) can be applied to obtain efficient alternatives in order to choose the best-compromise solution. The best solution with respect to the ideal point has the lowest value for LP (S) that will be the best-compromise solution. Obviously, the best-compromise solution may change with the values of the parameter p and the weights μ_j that are chosen by the DM.

Robust optimization approach

One way to deal with uncertainty is to conduct an optimization model that is "robust" to identify imprecise data changes (without the greater complexity of the original problem). Recently, robust optimization has been used as an optimization model that incorporates uncertainty, even when probabilistic knowledge of the phenomenon is incomplete. This type of optimization was first introduced by Soyster (1973) for linear programming problems. Although Soyster's method admits the highest protection, it is also the most conservative one in practice in the sense that the robust solution has an objective function value worse than the objective function value of the solution of a nominal linear optimization problem. To cope with the problem, Ben-Tal and Nemirovski (1999), El-Ghaoui and Lebret (1997), and El-Ghaoui et al. (1998) extended Soyster's method. They introduced a higher degree of non-linearity (conic quadratic problem), given the nominal problem in real problems. To overcome this computational difficulty, Bertsimas and Sim (2004) developed a new approach that keeps the linearity of Soyster's method and controls the level of conservatism.

Let's consider the following generic Deterministic Linear Problem (DLP):

$$\text{Maximize} \quad Z=cx$$
$$\text{Subject to} \quad \boldsymbol{Ax \leq b}, \quad \boldsymbol{x \geq 0}. \tag{4}$$

where $\boldsymbol{A}$**,** b and c are coefficients of matrix for technical, right-hand side and objective functions, respectively. If J_i is the set of coefficients in row i for matrix A, as that element is uncertain, then $a_{ij}, j\in J_i$ is modeled as a symmetric and bound random variable $\tilde{a}_{ij}$ as follows (see Ben-Tal & Nemirovski, 2000):

(5)

where $\varepsilon > 0$ defines a given uncertainty level and $\bar{a}_{ij}$ denotes the nominal (mean) value of uncertain data. η_{ij} is random variables that are symmetrically distributed within the interval of [-1,1]. So, the element of ãij is modeled as a bound, symmetric (but not necessarily uniform) random variable that takes values within $[\bar{a}_{ij}-\varepsilon\bar{a}_{ij}, \bar{a}_{ij}+\varepsilon\bar{a}_{ij}]$.

Bertsimas and Sim (2004) introduced a Gamma parameter for each constraint i (Γ_i) that is not necessarily an integer and takes the value of $[0,|J_i|]$ where $|J_i|$ is the number of uncertain data in a constraint i. Γ_i was considered as a *budget of uncertainty* and its role was to control the degree of conservatism (uncertainty).

According to the Eqs.4 and 5, the linear form for robust optimization can be rewritten as:

$$\text{Maximize} \quad Z=cx$$

(6)

At optimality, y_j will equal $|x_{ij}|$ for all j.

where z_i and p_{ij} are additional variables for each constraint of the robust problem. When the uncertainty level is non-zero and parameter $\Gamma i=0$, the greatest value is allocated to z_i and, the zero value is allocated to p_{ij}. Accordingly, in this case, the ith constraint is equivalent to that of the nominal problem

. It is reasonable that both parameters z_i and p_{ij} are ineffective in Eq. (6). In addition, while $\varepsilon=0$, robust problem changes to a nominal problem. It is reasoned that both parameters z_i and p_{ij} are zero in Eq. (6).

Formulation of multi-objective problem for agricultural land use planning

Notation

The following symbols are used in this section:

Index:

c : Index of crop: $c \in \{1, 2, ..., C\}$

s : Index of season: $s \in \{1, 2, ..., S\}$

p : Index of pesticides: $p \in \{1, 2, ..., P\}$

f : Index of chemical fertilizers: $f \in \{1, 2, ..., F\}$

Decision variable:

X_{cs}: allocated lands for cultivating the crop c during the season s

Uncertain productive resources:

TAW_s: quantity of available water for season s ($m^3 \times 10^6$)

Other productive resources:

TAL_s : total area of agricultural lands for cultivating the crop in the season s (hectares (ha))

Coefficients:

N_c: net profit per ha of land for crop c ($/ ha)

L_c: labor requirement per ha of land for crop c (Man-day / ha)

F_{cf}: amount of the fertilizer f required per ha of land for cultivating the crop c (kg / ha)

P_{cp}: amount of the pesticide required per ha of land for cultivating the crop c (kg / ha)

W_{cs}: amount of water requirement per ha of land for crop c during the season s (m^3 / ha)

M_c: machine hours requirement per ha of land for crop c (hours / ha)

The objective of functions of the proposed agricultural land which use MOP model (with the aim of sustainability) is to maximize economic development (farmer's gross margin), to minimize environmental pollution (fertilizers and pesticides) and water irrigation consumption, and to maximize employment opportunities.

Objectives

Maximize gross margin (economic indicator): The decision maker will try to maximize its expected gross margin. Maximization of net farm income can be expressed as

(7)

Maximize hired labor employment (social indicator): Because of the high unemployment rate in the surveyed areas, labor becomes major consideration for planting crop from the government perspective. Hired labor maximization is, thus, incorporated as another objective function in the study and is formulated as:

(8)

Minimize pesticides and chemical fertilizer consumption (environmental indicator): To maintain the productivity of the soil and on-farm costs by insect attacks, different types of pesticides *(p)* and fertilizers *(f)* must be used in different seasons. On the other hand, potential surface and ground water pollution by the excessive use of pesticides and chemical fertilizers have to be minimized for a sustainable agriculture system. Thus, the objective is to minimize these environmental costs and appear as:

(9)

(10)

Minimizing irrigation water consumption (environmental indicator): The selection of a combination of crops that utilizes the minimum water in each season is the main concern for resolving the water shortage problem. The objective is to minimize the total water irrigation consumption and is formulated as:

$$Min: Z_{9-10} = \sum_{c=1}^{c} W_{cs} X_{cs} \qquad \forall s \tag{11}$$

Minimizing machinery utilization (environmental indicator): spatial sustainability analysis combining soil special capabilities and suitability provides sound basis as governing criteria for maintaining the soil resource productivity over the long-run. Minimizing machinery utilization is a good objective for cropping area based on soil suitability and is formulated as:

(12)

Hard constraint

Hard constraints are the ones that must be satisfied completely. All above objectives (except) must be restricted to available source for each one. In addition, the constraint for utilization of total cultivable land in different seasons takes the form:

$$\sum_{c=1}^{C} X_{cs} \leq TAL_s \tag{13}$$

Modified uncertain data

There are many uncertain data points that arise from predictions of parameters in the above model. This study assumes that uncertainties are considered in the parameters of quantity of available water for each season *(TAW$_s$)*. Using Eq.5, the random form for this parameter can be rewritten as follows:

(14)

Where is the nominal value of quantity of available water for each season.

Aggregated modified robust reformulation

The constraint sets related to the uncertain parameter ( ) in the robust formulation using Eq.(6) can

International Journal of Agricultural Management and Development, 8(3), 365-375, September 2018.

be written as follows:

(15)

where Γ_s represents the seasonal water constraint which controlled the degree of conservatism in the constraint set a (for uncertain data). Z_s and P_s are additional variables for robust constraint *a*.

The application of the proposed model to the site under study demonstrates the reliability and flexibility of the model.

The problem situation

The researchers formulated the nominal MOP model and its robust counterpart for the right fringes of the Nekooabad irrigation network located in the province of Isfahan, Iran as presented in Fig. 1. The right fringes of the Nekooabad irrigation network includes a diversion dam called Nekooabad, a main canal located on right sides of the diversion dam, and branch canals. The branch canals transfer the irrigation water from the main canals to the agricultural areas in four regions: Mobarakeh, Nadjafabad, Lenjan, and Falavarjan. The study area covers 15,000 ha and is fed by the Zayandehrood river (the Nekooabad irrigation network). According to the report of Jihad-e Agriculture Organization (2010), this district has a high consumption of environmental contaminant inputs (particularly fertilizers and pesticides). Moreover, the river flow (Stochastic) in the resent years (2000-2012) has been very low, and water scarcity has been one of the most important issues in the management of the Nekooabad irrigation network. The economic situation has been the worst one in last decade due to high inflation and unemployment rates; therefore, all these issues were considered and expressed as 11 objectives in the MOP application.

Data

The sources of data are as follows: the District Statistical Yearbook (Dept. of Regional Planning and Development 2010), Jihad-e Agriculture Organization (unpublished results, 2008), Iranian Ministry of Energy (2003), and Isfahan Regional Water Organization (2008).

The crops are denoted as c = 1 for wheat, c = 2 for barley, c = 3 for corn, c = 4 for onion, c = 5 for potato, c = 6 for tomato, c = 7 for sunflower, c = 8 for sugar beet, c = 9 for canola, and c = 10 for cucumber. The 1st cropping season, s = 1, is defined as the period from April to October and

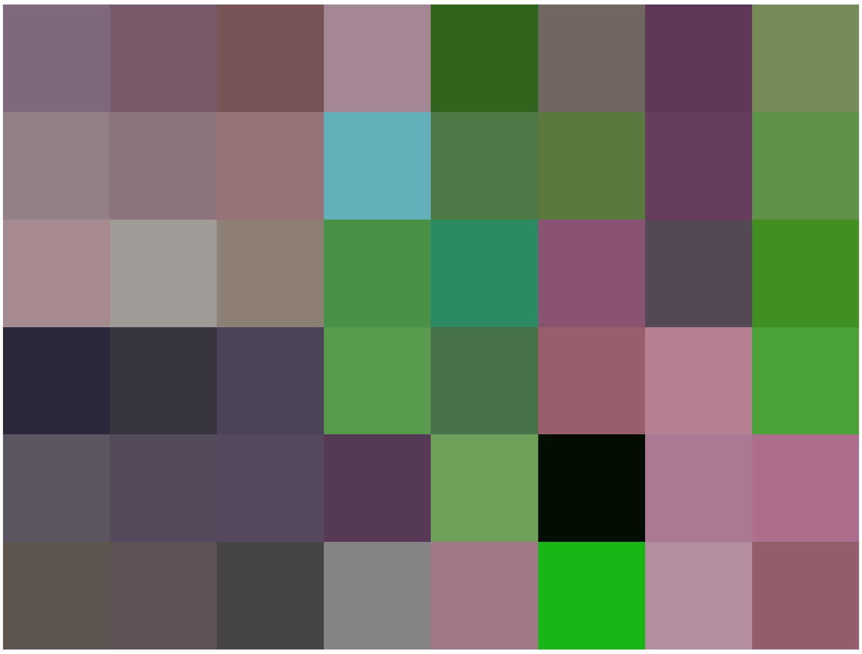

Figure 1. The Nekooabad agricultural irrigation water network in Isfahan Province, Iran (Source: Department of regional water of Isfahan Province).

Table 1
Descriptive Data

Crops	Wheat	Barley	Corn	Onion	Potato	Tomato	Sunflower	Sugar beet	Canola	Cucumber
Coefficients										
M_c	22	23	25.5	15	23	29	26	26.5	30	23
L_c	34.54	39.81	25.8	62.32	77.08	87.03	39.96	28.9	14.27	77.36
F_{c1}	0.2521	0.2138	0.2513	0.4227	0.4498	0.3627	0.21936	0.43966	0.3538	0.3076
F_{c2}	0.3171	0.2711	0.6533	0.6856	0.5994	0.5119	0.38536	0.63625	0.484	0.5803
F_{c3}	0.0094	0.0125	0.0039	0.0344	0.064	0.0133	0.01862	0.03101	0.0125	0.0403
P_{c1}	1.192	0.283	6.285	3.524	1.424	4.349	0.637	2.698	1.178	2.927
P_{c2}	0.457	0.264	0.039	4.775	1.142	2.969	0.001	2.354	0.782	3.741
P_{c3}	0.293	0.095	0	2.157	0.972	0.655	0	0.719	0	1.857
W_{c1}	7966	6900	0	11683	0	0	0	0	0	0
W_{c2}	0	0	11283	0	10400	11483	10116	15816	7500	7733
N_c	363	312	616	1924	1419	1357	496	576	429	1463

Note: F_{c1} = Amount of potash required for production (kg / ha), F_{c2} = Amount of nitrogen fertilizer required for crops (kg / ha), F_{c3} = Amount of phosphate fertilizer required for production (kg/ ha),P_{c1}= Amount of herbicide required for production (kg / ha),P_{c2}=Amount of pesticide required for production (kg / ha), P_{c3}=Amount of fungicides required for production (kg / ha). N_c= Gross margin per unit of ha ($/ha)

the 2nd season (s = 2) is defined as the period from November to March. The data description for productive resource utilization and gross margin per unit of ha are given in Table 1.

A Monte Carlo simulation was employed to generate a random number for simulating the amount of available water (Hardaker et al., 2004). The simulated amount of available water for this irrigation network are 92 ($\overline{TAW}_1$), and 32 ($\overline{TAW}_2$) million m³ (M.C.M).

RESULTS AND DISCUSSION

This section shows the results of the compromise solutions obtained from the MOP under nominal problem and its robust counterpart for the Nekooabad irrigation network, presented in Figure 1. The nonlinear problem was solved using the GAMS/BARON global optimization solver (Sahinidis & Tawarmalani, 2005).

Table 2 summarizes some of the important results obtained through the nominal (i.e. all Γ=0) and

Table 2
Annual Areas Allocations for Nominal and Robust Mop

	Areas (ha)			
Crops	Current	Nominal	Robust	
			Γ=0.2	Γ=0.6
Wheat	7161	3709	1129	1950
Barley	2288	5076	7675	6466
Corn	283	182	763	703
Onion	403	78	35	103
Potato	1590	661	36	0
Tomato	140	1594	983	1391
Sunflower	67	248	110	0
sugar beet	495	0	0	0
Canola	178	85	38	0
Cucumber	171	229	1097	717
Total	12776	11864	11865	11330

Table 3
Final Values of the Objectives for Nominal and Robust MOP

	Current	Nominal		Robust			
Objectives			**Change%**	**Γ =0.2**	**Change%**	**Γ =0.6**	**Change%**
Gross margin	7356353	6790742	-7.69	6401194	-12.98	6293140	-14.45
Manpower	538335	558335	3.72	544470	1.14	525816	-2.33
Machine	288190	279890	-2.88	279890	-2.88	267914	-7.04
Phosphate	3650	3130	-14.25	2880	-21.10	2820	-22.74
Nitrogen	4903	4207	-14.20	4183	-14.68	4029	-17.83
Potash	240	180	-25.00	173	-27.92	153	-36.25
Herbicide	17344	16085	-7.26	16085	-7.26	17085	-1.49
Pesticide	9988	9829	-1.59	9829	-1.59	9929	-0.59
Fungicides	5495	3850	-29.94	3850	-29.94	3650	-33.58
Water (s=1)	77.54	65.49	-15.54	62.36	-19.58	61.36	-20.87
Water (s=2)	32.5	32.17	-1.02	30.15	-7.23	29.45	-9.38

robust (ε=0.05 and Γ=0.2 and 0.6) problem. As the results demonstrate, the most optimal annually allocated area in nominal problem is for barley production with the values of 5076 ha, while the largest areas have been allocated to wheat (7161 ha) in the existing plan. This is due to the high total gross margin per unit of agricultural areas for wheat production. On the other hand, the amount of water requirement for barley is less than wheat (see Table 1). Thus, in the nominal MOP, wheat production decreases to 3709 and the barley production increases to 5076. Because of the low gross margin per unit of ha, high requirements of pollution resources (fertilizers and pesticides), and high requirement of irrigation water in sugar beet production, optimal annually allocated areas in both problems (nominal and robust) are zero. The total allocated areas is worse, as the degree of conservatism (Γ) increases from 11865 to 11330. In the level of Γ= 0.6, four crops (potato, sunflower, sugar beet, canola) are eliminated from the optimal cropping pattern. This is a logical finding, because the optimal cropping pattern tends toward the crops that have higher gross margin and lower water requirements, and because available water is an uncertain data in this study.

Table 3 summarizes the final value of the objectives for MOP obtained from the nominal (i.e. all Γ=0) and robust (ε=0.05 and Γ=0.2 and 0.6) problems. As can be seen, in the nominal MOP, all final values are decreased except hired labor employment objective (manpower) that was a maximizing objective. It is a suitable condition, because there is an appropriate change in other objectives (negative for minimizing and positive for maximizing). Accordingly, all objectives are improved except the total gross margin. This shows that the farmers have paid attention to maximizing profit without agricultural sustainability in the studied region. In the robust form, the gross margin objective decreases as the degree of conservatism (Γ) increases (similar to the gross margin reported by Sabouhi and Mardani, 2013). In addition, Table 4 demonstrates that as the degree of conservatism is increased, the irrigation water consumption decreases in both seasons. For example, irrigation water consumption decreases from 62.36 to 61.36 (m3×106/Year) with an increased degree of conservatism from 0.2 to .06 in season 1.

Model calibration

Model calibration refers to adjusting the model and parameters to bring the model outputs as close to the observed values as possible. To calibrate the proposed model, the authors used time series data of model parameters (18-year time series data) and ran the model using these data. We used some statistical criteria to make a comparison between the model outputs and observed values of variables, including the coefficient of determination (R2), Root Mean Square Error (RMSE), and Average Percent Error (APE), which were estimated to be 0.58, 0.016, and 0.015, respectively.

Evaluating the model through Monte Carlo simulation

To examine the quality of the proposed model, 1000 simulations of random uncertain data were run with the parameters of amount of available water ($\overline{TAW}_s$), and nominal (i.e., all Γ=0) and robust (ε=0.05 and p=0.1) problem solutions were compared. Random numbers were generated using Simetar Excel add-in software that easily and quickly selects the distribution that best fits the data.

A Monte Carlo simulation was also implemented for analysis. The percentage of cases in which the solution was determined as infeasibility was recorded. A normal distribution within the interval was assumed with a 95% coverage (i.e. 1.96 times the standard deviation of the distribution) for simulation runs. The Monte Carlo simulation determined probabilities for infeasibility in nominal and robust problems as percentages of 63.2 and 18.6%, respectively, assuming a 95% coverage normal distribution. Chung et al. (2009) reported 24% and 32% infeasibility for the nominal and robust problems, respectively.

Conclusion

This paper illustrated the application of multiple-objective programming to optimal allocation of agricultural areas for the right fringes of the Nekooabad irrigation network located in nominal and robust form. The robust form of MOP was presented to support the allocation of agricultural areas under uncertainty. The primary uncertainty parameter of the model was quantity of available water for each season. In the application, the researchers solved the model for sensitivity analysis of the levels of robustness using GAMS software. The results indicate that as the degree of conservatism (Γ) increases, the optimal solution structure changes. The optimal total gross margin in the robust problem indicates that the optimal total gross margin decreases with higher robustness levels. To compensate for the loss of gross margin of farmers in this pattern, efficiency enhancement policies are emphasized.

A Monte Carlo simulation was employed to analyze the probabilities of infeasibility in the nominal and robust problems. It was determined that the probabilities of viability in the nominal and robust problems were as 63.2 and 18.6%, respectively, assuming a 95% coverage under normal distribution. This indicates that the proposed model is both reliable and flexible. Thus, it is recommended to use the allocation model presented in robust approach for more protection of system against uncertainty. Moreover, the proposed model offers reduction in the area under cultivation. So, it is recommended to use reduced irrigation water availability policies to reduce the total cultivated area.

As a recommendation for further works, the proposed model and its decisions need to be better represented. For example, this study is based on linearity assumption of constraint. However, if water irrigation requirements of the Nekooabad irrigation network are completely satisfied, then there will be non-linearity in the relationship between crop yield and irrigation water, resulting in a logarithmic relation for greater volumes of irrigation water. Therefore, this aspect should be considered in future work.

ACKNOWLEDGEMENTS

The authors acknowledge the research support from Mamoud Sabouhi (Professor of Agricultural Economics, University of Ferdowsi Mashhad); and appreciate the valuable and thoughtful feedback from Jihad-e Agriculture Organization.

REFERENCES

Bell, S., & Morse, S. (2008). Sustainability indicators: Measuring the immeasurable? London, Earthscan.

Ben-Tal, A., & Nemirovski, A. (1999). Robust solutions to uncertain programs. Operations Research Letters, 25,1-13.

Ben-Tal, A., & Nemirovski, A. (2000). Robust solutions of linear programming problems contaminated with uncertain data. *Journal of Mathematical Programming, 88,* 411-424.

Bertsimas, D., & Sim, M. (2004). The price of robustness. *Journal of Operations Research Letters, 52*(1), 35–53.

Chang, Y.C., Hung, F.W., & Lee, M.T., (2008). A system dynamic based DSS for sustainable coral reef management in Kenting Coastal Zone, Taiwan. *Ecological Modeling, 211* (1), 153–168.

Chen, H., Yang, W. G., Liang, X. Y., & Wang, T. (2010). Multi-scale modeling of land use based on the MAS from field to village: A case study for Mengcha Village of Mizhi County of Shaanxi Province. *Geographical Research, 29,* 1519–1527.

Chung, G., Lansey, K., & Bayraksan, G. (2009). Reliable water supply system design under uncertainty. *Environmental Modelling and Software, 24*, 449–462.

Cohon, J.L. (1978). Multi objective programming and planning. Academic Press, New York.

Eshraghi Samani, RE, & Poursaeed, A. (2015). Cropping pattern and comparative advantage of agricultural products in Ilam Province. *International Journal of Agricultural Management and Development, 5*(3), 235-243.

Department of Regional Planning and Development (2010). District statistical yearbook (Annual time series data from 1986 to 2009), Isfahan, Iran.

Diamond, J.T., & Wright J.R. (1989). Efficient land allocation. *Journal of Urban Planning and Development, 115*, 81–96.

El-Ghaoui, L., & Lebret, H. (1997). Robust solutions to least-square problems to uncertain data matrices. *SIAM Journal on Matrix Analysis and Applications, 18*, 1035-1064.

El-Ghaoui, L., Oustry, F., & Lebret, H. (1998). Robust solutions to uncertain semidefnite programs. *SIAM Journal on Optimization, 9*, 33-52.

Gibert, K.C., Holmes, D.D., & Rossenthal, R.E. (1985). A multi objective discrete optimization model for land allocation. *Management Science, 31,* 1509–1552.

Gomez-Limon, A., & Riesgo, L. (2009). Alternative approaches to the construction of a composite indicator of agricultural sustainability: An application to irrigated agriculture in the Duero basin in Spain. *Journal of Environmental Management, 90*, 3345–3362.

Hafkamp, W., & Nijkamp, P. (1968). Integrated economic-environmental-energy policy and conflict analysis. *Journal of Policy Modelling, 8,* 551-576.

Hansen, J. (1996). Is agricultural sustainability a useful concept? *Agricultural Systems, 50*(2), 117-143.

Hardaker, J.B., Huirne, R.B.M., Anderson, J.R., & Lien, G. (2004). Coping with risk in agriculture. (2 Ed.), CABI Pulishing, London, UK, p. 332

Iranian Ministry of Energy, Office of Dams and Agricultural Irrigation Networks Control. (2003). Statistical Report of Long-Term Development Strategies for Iran's Water resources, Unpublished result. Tehran, Iran.

Isfahan Regional Water Organization, Department of Equipment and Development of Agricultural Irrigation Networks. (2008). Selected Water Resources Data, Unpublished result. Isfahan, Iran.

Jihad-e Agriculture Organization, Soil and Water Management Department. (2010). Statistical Report of Irrigation Systems in Esfahan Province, Unpublished result. Isfahan, Iran.

Larimian, T., Zarabadi, Z., & Sadeghi, A. (2013). Developing a fuzzy AHP model to evaluate environmental sustainability from the perspective of Secured by Design scheme-A case study. *Biological Sciences, 7*, 25–36.

Monteith, J.L. (1990). Can sustainability be quantified? *Indian Journal of Dry land Research and Development, 5* (1), 1-5.

Morse, S., McNamara, N., Acholo, M., & Oknoli, B. (2000). Visions of Sustainability. Ashgate, Hampshire, UK, pp. 5–45.

Romero, C., & Rehman, T. (2003). Multiple criteria analysis for agricultural decisions. 2th Edition, British Library cataloguing, UK, pp47-61.

Sabouni, M., & Mardani, M. (2013). Application of robust optimization approach for agricultural water resource management under uncertainty. *Journal of Irrigation and Drainage Engineering, 139,* 571–581.

Sahinidis, N., & Tawarmalani, M. (2005). GAMS/BARON Solver Manual. Arki Consulting Development, Bagsvaerdvej, Denmark, pp.233.

Seppelt, R., & Voinov, A. (2003). Optimization methodology for land use patterns valuation based on multiscale habitat pattern comparison. *Ecological Modeling, 168* (3), 217–231.

Soyster, A. L. (1973). Convex programming with set-inclusive constraints and applications to inexact linear programming. *Operations Research, 21,*1154–1157.

Stewart, T.J., Janssen, R., & Herwijnen, M. (2004). A genetic algorithm approach to multibjective land use planning. *Computers & Operation Research, 31,* 2293–2313.

Tiwari , D.N., Loof , R., & Paudyal, G.N. (1999). Environmental-economic decision-making in lowland irrigated agriculture using multi-criteria analysis technique. *Agricultural Systems, 60,* 99-112.

Ying-bin, H., & Wei-min, C. (2016). Linking a farmer crop selection model (FCS) with an agronomic model (EPIC) to simulate cropping pattern in Northeast China. *Journal of Integrative Agriculture, 15*(10), 2417-2425.

Yu, Q. Y., Wu, W. B., Tang, H. J., Yang, P., Li, Z. G., Xia, T., Liu, Z. H., & Zhou, Q. B. (2013). An agent-based model for simulating crop pattern dynamics at a regional scale: Model framework. *Scientia Agricultura Sinica, 46,* 3266–3276.

Yunlong, C., & Smit, B. (1994). Sustainability in agriculture: A general review. *Agricultural Ecosystem and Environment, 49* (2), 299–307.

Zekri, S., & Romero, C. (1993). Public and private compromises in agricultural water management. *Journal of Environmental Management, 37*, 281-290.

How to cite this article:

Mardani, M., Ziaei, S., & Nikouei, A. (2018). Optimal cropping pattern modifications with the aim of Environmental-Economic decision making under uncertainty. *International Journal of Agricultural Management and Development, 8(3), 365-375.*

URL: http://ijamad.iaurasht.ac.ir/article_542558_85d51a0b26c9a956ec5b306ac7fc19f4.pdf