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Suitability of Multiple - Criteria Decision Making Simulations to Study Irrigation Water Demand: A Case Study in the Doroudzan River Basin, Iran

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Abstract: The main contribution of this study is effort to design a simulation model to analyses the differential impacts of pricing policy for irrigation water in the Doroudzan basin in the south of Iran. For this purpose, Multi-Attribute Utility Theory (MAUT) mathematical programming models were used. The analysis of water pricing policy impacts clearly demonstrate that farmers display different behavior patterns related to this natural resource. Also, patterns of consumption vary along the demand curves as a result of increases in the water price. Inelastic price segments of the water demand curves coincide with prices at which the farmers are insensitive to resource price increases, maintaining their usual crop mixes without any substantial change. On the other hand, the elastic segments correspond to those water tariffs that encourage farmers to replace their current crops with others that have lower water requirements. This highlights the importance of implementing a differential analysis to study the impact of water pricing due to the existence of a variety of responses among different groups of farmers. The influence of the elasticity of water demand in reducing water consumption obtained through resource pricing is remarkable. It can be seen that in the elastic segments of the curves the increase in the price of water produces great savings in consumption due to changes in crop mixes, while in the inelastic segments, tariff rises do not result in significant water savings, since farmers are not induced to change their crop plans. This is the reason why the greatest savings are obtained with pricing scenarios in elastic segments of the water demand curves. To produce any significant further saving in the amount of water consumed by group of farmers it would be necessary to apply tariffs higher than the threshold price.

Key words: Simulation · Multi-criteria programming · Multi-attribute utility technique · Irrigation water demand · Water pricing policy · Iran

INTRODUCTION

The dry areas of Southern Iran face severe challenges due to limited opportunities for the exploitation of new sources of water coupled with the constantly rising demand for water clearly demonstrates the growing relative shortage of this resource. The rising of population in Iran puts significant pressure on authorities and infrastructures to provide water. Without improvement in water management, irrigation demand will continue to increase, water supplies will diminish and the population will decay infrastructures [1,2].

It is evident that these pressures will require more effective allocations and use of existing resources. But, observations indicate that scarce water resources of the region are poorly managed and inefficiently used [3,4].

Iranian irrigation water users currently pay a price for water that it does not reflect the full cost of providing water. In fact, the most of financial costs are met by the national budget and form a hidden subsidy to farmers in the irrigable areas.

Economic theory explains that in general price and quantity are linked by an inverse relation. This is true also for water, but this function is not linear and not constant, since price is only one of many variables which influence the amount of water used. The theory shows that water pricing can be used as a means of enhancing water use efficiency in irrigation [5-10]. It is well acknowledged that to introduce incentives, tariffs should incorporate a volumetric element.

The fundamental role of prices is to help allocate water among competing uses and users and achieve to water use efficiently. As to this it is clearly pointed out

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that the principle of recovery of the costs of water services should be adopted by users.

This paper aims to contribute to this policy discussion by deriving a water- demand function that illustrates the impact that a policy based upon water pricing might have on agricultural production.

Therefore, researchers propose a methodology of mathematical programming model that simulates for different scenarios water prices. Therefore, multiple criteria decision-making techniques (MCDM) are useful tools to explore different management options. These techniques are used widely to solve multi-objective and multi-resource decision making problems where conflicts exist among different objectives [11]. MCDM techniques permit optimization of several objectives in many different logical formulations [12]. A multi-criteria approach has been used extensively to solve diverse decision problems including risk assessment in agricultural systems [13]. So, simulation is proposed as a suitable technique for implementing the multi-criteria approach that empirically applied for the analysis of the potential impact of the implementation of water pricing in the is irrigable area in the Doroudzan Basin in the south of Iran.

MATERIALS AND METHODS

Although the basic principles of classical economic theory assume that decision-makers behave as profit maximizes but, many decision support systems in agricultural enterprises use a conventional linear programming approach to optimize a single objective function such as total gross margin. However, as agricultural systems become more complex, multiple objectives that are in conflict with each other need to be addressed. Many authors such as Harman *et al.* [14], Gasson, [15], Smith and Capstick [16], Harper and Eastman [17], Kliebenstein *et al.* [18], Patrick and Blake [19], Cary and Holmes [20]; Berbel and Rodrı´guez, [21], Costa and Rehman, [22] and Willock *et al.*[23] have shown the complexity of the farmers' decision-making process through empirical studies that have demonstrated that they consider more than one attribute in their utility functions. Therefore, real-life observations refute this simplification. According to this perspective, farmers' decision-making process is simultaneously driven by various attributes related to economic, social, cultural and natural dimensions. The solution to these complex decision problems requires the use of mathematical techniques that are formulated to take into account conflicting objectives include maximization of total gross margin, maximization of leisure, minimization of risk and other managerial problems, minimization of indebtedness, etc. In this framework a decision-maker tries to satisfy, as far as possible, all these criteria at the same time.

Keeney and Raiffa [24] developed Multi-Attribute Utility Theory (MAUT). Ballestero and Romero [25] argued that this technique has the soundest theoretical structure of all the multi-criteria techniques. Herath [26] and Hardaker *et al.* [27] believed that at the same time, from a practical point of view, the main drawback to this approach comes from the elicitation of the multi-attribute utility function. According to this multi-criteria paradigm the observed differences in decision-making among farmers which operate in the same production area are due to differences in the objective functions, i.e. in the attributes and in their weights, which represent the relative importance of the attributes, more than to disparities in resources requirements or endowments, such as land, capital and labor or water availability. In order to simplify this process, some assumptions need to be made about the mathematical features of the utility function. In most cases, additive and linear utility functions have been adopted to simulate farmers' behavior in a multi-attribute framework [21,28-31]. As Hwang and Yoon [32] point out: "theory, simulation computations and experience all suggest that the additive method yields extremely close approximations to very much more complicated non-linear forms, while remaining far easier to use and understand". Go´mez-Limo´n and Riesgo [31] argued that if the attributes are mutually utility-independent and takes the additives form:

$$U(x_1, x_2,... x_n) = \Sigma w_i u_i(x_i),\ i = 1, 2,..., n \qquad (1)$$

or takes multiplicative form:

$$U(x_1, x_2,... x_n) = \{\Pi\ (Kw_i u_i(x_i) + 1) - 1\}/ K,\ i = 1, 2,..., n, \qquad (2)$$

Keeney [33], Keeney and Raiffa [24] and Fishburn [34] note that $0 = w_i = 1$ and $K = f(w_i)$. If the $\Sigma w_i = 1$, then $K= 0$, thus the utility function is additive.

Since the elicitation of the multiplicative form makes great demands on the introspective capacity of the decision-maker, it is usually assumed that $\Sigma w_i = 1$, so that the utility function is additive. We therefore adopt this simplification in the elicitation of the additive utility function. Mathematically, the expression (1) in its simple form becomes:

$$Uj = \Sigma w_i u_i(r_j), \ i = 1, 2, ..., m, \quad (3)$$

Where Uj is the utility value of alternative j, w_i is the weight of attribute i and $u_i(r_j)$ is the value of the additive utility due to attribute i for the alternative j.

The aggregate utility function, assumed linear, requires normalization since different units are involved. The selection of objectives and the estimate of the related weights can be conducted in a non-interactive approach by following a methodology proposed by Sumpsi *et al.* [35], improved by Amador *et al.* [36] and applied by Berbel and Rodriguez [21], Go´mez-Limo´n and Berbel [29], Go´mez-Limo´n and Arriaza [28], Go´mez-Limo´n and Riesgo [31] and Go´mez-Limo´n and Martınez [30]. Given this justification for the use of the additive utility function, Go´mez-Limo´n and Berbel [37] and Go´mez-Limo´n and Riesgo [31] took the further step of assuming that the individual attribute utility functions are linear. Hence, the expression (3) becomes:

$$Uj = \Sigma w_i \ (r_{ij}), \ i = 1, 2, ..., m, \quad (4)$$

Where r_{ij} is the value of attribute i for alternative j.

Alternatively, objectives and relative weights can be derived through interaction with the decision makers.

Both Sumpsi *et al.* [38,39] and Amador *et al.* [36] propose weighted goal programming as a methodology for the analysis of decision making. Go´mez-Limo´n and Berbel [40] and Berbel and Rodriguez [21] believed that this methodology has been successfully implemented on real agricultural systems. Briefly, Go´mez-Limo´n and Berbel [37] declared the methodology can be summarized as follows:

At first, tentatively establish a set of objectives that may be supposed to be most important for farmers. Then, determine the pay-off matrix for the above objectives. And finally, using this matrix estimate a set of weights that optimally reflect farmers' preferences.

The first step thus consists of defining a tentative set of objectives $f_1(X)$... $f_i(X)$... $f_n(X)$ (e.g. profit maximization, risk minimization and management complexity minimization).

Then, the second step is the calculation of the pay-off matrix, which has the following formulation:

	$f_1(X)$	$f_2(X)$	... $f_i(X)$	... fq(X)
$f_1(X)$	f_1^*	f_{12}	f_{1i}	f_{1q}
$f_2(X)$	f_{21}	f_2^*	f_{2i}	f_{2q}
$f_i(X)$	f_{i1}	f_{i2}	f_i^*	f_{iq}
$f_q(X)$	f_{q1}	f_{q2}	f_{qi}	f_q^*

The pay-off matrix and the corresponding crop mix has been determined using the objective functions and constraint equations. The pay-off matrix for the goals illustrates the degree of conflict between the different goals.

The elements of the pay-off matrix were obtained by optimizing each of the objectives individually and then calculating the values of the remaining objectives using the solution vector of the decision variables. Thus, f_{ij} is the value of the i attribute when the j^{th} objective is optimized. This matrix contains valuable information pertaining to the existence or otherwise of conflicts between the objectives. The existence of conflicts enables us to use multiple decision criteria methods that combine all the objectives into a multi-criteria model. The diagonal elements of the pay-off matrix are the optimum values for each individual goal and the corresponding off-diagonal elements are the values of the other objectives evaluated using the basic elements of the optimized solution vector.

Attached to the above matrix a column has been included to indicate the values achieved for the different objectives in the real world.

These data are now used to estimate objective weights that optimally reflect farmers' preferences.

If the system does not result in a set of w (weights of each objective that represent the actual behavior of the farmer), it will be necessary to search for the best possible solution. For this purpose this study takes the work of Romero [41] and therefore weighted goal program with percentage deviational variables can be formulated. The goal programming model solves the multiple objective problems by introducing the objectives into the problem as constraints and setting targets to be achieved. The objectives are included in the problem by adding positive (p_i) and negative (n_i) deviation variables that describe over-achievement and under-achievement of each goal.

It is therefore necessary to solve a problem by minimizing the sum of deviational variables that find the closest set of weights;

$$\text{Min: } \Sigma \ (n_i + p_i)/f_i$$

Subject to:

$$\Sigma \ w_i f_{ij} + n_i - p_i = f_i, \ i= 1, 2,... q \text{ and } \Sigma \text{ wi} = 1$$

As Dyer [42] demonstrates the results of solving these equations are the weights (wi) and, these weights are consistent with the following separable and additive utility functions:

$$U = \sum_{i=1}^{q} \frac{w_i}{k_i} f_i(x) \quad (5)$$

Where, k_i is a normalizing factor and it must range between 0 and 1 because this utility surrogate needs to fulfill the requirements of being an additive MAUF. Then, these weights can be used to build a MAUF adjusted to the expression;

$$U = \sum_{i=1}^{n} w_i \frac{f_i(x) f_{i*}}{f_i^* - f_{i*}} \quad (6)$$

Where, fi^* is the maximum value for objective i in the pay-off matrix developed for the criteria considered and fi_* is the minimum value.

The normalizing factor in (6) is thus the difference between the maximum (fi^*) and minimum (fi_*) values for objective i in the pay-off matrix developed for the criteria considered.

The multi-objective problem described in this paper consists of three objective functions: Maximization of profit, risk minimization and minimization of hired labor as follows:

- Maximization of total gross margin (TGM), as proxy for short run profit. In calculating the gross margin of each crop (GMi), the water cost has not been included. The total gross margins, TGM considered are thus equal to the initial gross margins, GM_i (with zero volumetric tariff, C_{wi}) less the amount paid for water (water consumption, REQ_i for each crop, X_i multiplied by the tariffs) for each water price and interest payments for received loans ($r_j l_j$).

$$\text{Max: TGM} = \Sigma\,(GM_i - C_{wi}.REQ_i.X_i\,) - r_j l_j \quad (7)$$

- Risk is always present in any agricultural system because agricultural production is subject to price and yield fluctuations. Many authors such as Hardaker *et al.* [43], Berbel [13] and Pannel and Nordblom, [44] have proved the existence of risk-averse behavior in farmers' decision-making processes. Decision making therefore takes into consideration not only the classical objective of profit but also considers the risk implied by the selected crop plan.

In this study database developed over the period 2000/2001-2004/2005 was used to assess total risk in terms of the variance, mathematically:

$$\text{Min: Total risk} = x_i^t\,[\Sigma]x_i, \quad (8)$$

Where $[\Sigma]$ is the variance/covariance matrix of gross margins from the panel data (constant 2005 RIALs) and x_i is the crop decision vector. This approach allows risk reduction by diversification among crops with negative covariance.

- Minimization of hired labor (TL) has the aim of reducing the level of applied hired labor in spring and summer as labor intensive seasons. This objective implies not only a reduction in the cost of this input but also an increase in leisure time and the reduction of managerial supervision. The expression of TL is obtained in the following way:

$$\text{Min: TL} = \Sigma TL_i X_i,\ i = 1, 2,..., n \quad (9)$$

Where TL_i is the labor required by each crop (i).

The management options to achieve the above objectives consist of selection of an appropriate mix of crops and appropriate allocation of water for irrigation.

Constraints: Each followed resource constraint divided to four constraints for four seasons. Where in each season available these resources for all crops must be less than or equal to the total these resources available to the farm type. Constraints imposed on the model include as follows:

a) Land: The sum of all crop areas is equal to the total available area:

$$\Sigma\, X_i \le A_j,\ i = 1, 2,..., n,\ j = 1,2,3,4 \quad (10)$$

Where, subscript i represents the number of crops in each season and subscript j represents the number of seasons.

b) Irrigation water: Total crops water use in the irrigation areas should not exceed total allocation in a given season (Wj):

$$\Sigma\, REQ_i\, X_i \le Wj,\ i = 1, 2,..., n,\ j = 1,2,3,4 \quad (11)$$

c) Capital: The sum of all crop required capital ($\Sigma C_i.X_i$) is equal to the total available capital (K_j), earned income (R_j) through sale of crops and available one unit of loan (l_j) in each season:

$$\Sigma\, C_i.X_i - R_j - l_j \leq K_j,\ i = 1, 2,..., n,\ j = 1,2,3,4 \quad (12)$$

$$R_j = \Sigma\, GM_i.X_i,\ i = 1, 2,..., n,\ j = 1,2,3,4 \quad (13)$$

d) Rotation: One of the most important points under discussion in agricultural ecosystems is sustainability of agricultural land management. Crop rotation is one of the ways that may have a special effect on sustainable land management. Agronomically it is regarded as sound policy leads to an increase in the product's yield in comparison with continuous cropping in a piece of land. This limits the cultivated area for a crop to a maximum of 50% of total available area and applies to all crops:

$$\Sigma(X_i - X_j) \leq 0\ i = 1, 2,... n,\ j = 1,2... m \quad (14)$$

f) Market: In this study some of the crops such as tomato, onion, cabbage, carrot and sugar beet need to be produced in quantities that will demand without price distortions. We put an upper limit based upon the maximum historical cultivation of these crops in the period 2000/2001-2004/2005.

$$X_i = M_i,\ i = 1, 2,..., 5 \quad (15)$$

g) Rules and regulations: Some of the crops (e.g. rice and also corn in dry years) are subject to agricultural policy, rules, regulations and cultivation limits that affect them for cultivation.

$$X_i = L_i,\ i = 1, 2 \quad (16)$$

The following activities are used in model: X_1: Acreage of wheat (ha), X_2: Acreage of barley (ha), X_3: Acreage of rice (ha), X_4: Acreage of corn (ha), X_5: Acreage of tomato (ha), X_6: Acreage of onion (ha), X_7: Acreage of sugar beet (ha), X_8: Acreage of carrot (ha), X_9: Acreage of cabbage (ha).

It may be suggested that the problem of decision making that faces every individual irrigator in the short term (i.e. annual crop mix decision) can be simulated through a mathematical programming model whose objective function is the MAUF based on the weights vector (wj) calculated in each case, subject to the various technical and institutional constraints that need to be fulfilled.

Objective weighting and utility function elicitation: Once the basic models are built, they are solved using the LINDO and LINGO packages and optimized successively for the individual objectives proposed: TGM maximization and VAR and TL minimization. Then, the pay-off matrix and the corresponding crop mix was determined using the three objective functions (7)–(9) and constraint equations for each group of farmers.

Then, modeling irrigation water demand at basin level proposed would be outlined as follows:

$$\text{Max:}U(X) = W_{TGM}.\ K_{TGM}.TGM(X) - W_{VAR}.\ K_{VAR}.VAR(X) - W_{TL}.\ K_{TL}.TL(X) \quad (17)$$

Where W_{TGM}, W_{VAR} and W_{TL} are the weights estimated for the different objectives considered by the producer, K_{TGM}, K_{VAR} and K_{TL} are the normalizing factors. Thus, in this basic model the constraints linked with land and water availability are explicitly pointed out.

Validation of models: O'Keefe *et al.* [45] argued that validation refers to building the correct model', i.e. establishing that a model achieves an acceptable level of accuracy in its predictions. Harrison [46] pointed out that tests of data validity, conceptual validity and operational validity may be conducted to determine whether the structure of the model is appropriate for its intended purpose. Qureshi *et al.* [47] believed that the validation process has largely been confined to checking operational validity, or the ability of a model to mimic the real system.

Harrison [48] and O'Keefe *et al.* [45] noted that model validation methods include testing for predictive ability, assessment for face validity (including Turing tests), comparison against performance standards and examination of scope validity.

Qureshi *et al.* [47] point out that because the model is a simplification and abstraction from the real system, the performance levels predicted by the model will differ from those of the real system. Thus, validation is a matter of degree rather than a process with a clearly identifiable finishing point. Therefore process continues until sufficient confidence is built up in the model to use it for practical purposes. O'Keefe *et al.* [45] argued that the acceptable performance range should be specified during model development.

Researchers in this study adopt and employed the work of Qureshi *et al.* [47] that compares the real situation (observed) with the data simulated by the models for the current scenario.

Scenario simulations: The basic model described above was built to simulate the impacts of the various pricing scenarios. Then, researchers estimate different water demand functions in the case study area; one for each homogeneous group. Go´mez-Limo´n and Riesgo [31] for this purpose applied the simulation model the following alternatives:

- Substitution of water-intensive crops by others with less need for water.
- Cessation of irrigation and introduction of rain-fed crops.

In this study, authors have taken the work of Go´mez-Limo´n and Riesgo [31] but, another alternative be added that defined as follows:

- Substitution of full irrigation method by methods with less need for irrigation water or introduction of water stressing or deficit irrigation.

When the corresponding simulation models have been built, then the method of simulating farmers' behavior as a reaction to the water pricing policy consists of parametrising the water price. Water pricing is currently based on a fixed sum per unit of irrigated surface, like most irrigated areas in Iran. In this study pricing policy of irrigation water consists of parametrising the water price through zero to one hundred times of current tariff per m^3/ha that it is increased progressively.

Aggregation bias problem: Hazell and Norton [49] believed that the final result of putting a set of farms in a unique programming model is that the value obtained for the objective function is biased upward, overestimates the mobility of resources among the production units and finally, the values obtained for decision variables and combinations of resources tend to be unachievable in real life.

Therefore, classification of farmers into homogenous groups using cluster analysis is the most efficient method.

Go´mez-Limo´n and Riesgo [31] assumed that in a homogeneous area the differences in the crop mix among farmers are mainly caused by their different management criteria (utility functions) rather than by other constraints such as land quality, capital, labor or water availability. Thus, the surface (in percentage) devoted to the different crops (proxies of the real criteria) is used as classification variables to group farmers using the cluster technique. So, once the homogeneous groups of producers have been defined for actual data (crop mix), we can assume that all elements (farmers) within each group will behave in a similar way if policy variables change.

In this study, to avoid aggregation bias resulting from lumping together farmers with significantly different objective functions, researchers may also note that the farmers were classified by considering the chi-squared distance among actual crop mixes, expressed in percentages, as a measurement of distance and using the Ward method (minimum variance) as the aggregation criterion.

Therefore, clustering performed by using hierarchical clustering method. Hierarchical clustering builds (agglomerative), or breaks up (divisive), a hierarchy of clusters. The traditional representation of this hierarchy is a tree (called a dendrogram), with individual farmers at one end and a single cluster with every farmer at the other. Agglomerative algorithms begin at the top of the tree, whereas divisive algorithms begin at the bottom. This method builds the hierarchy from the individual farmers by progressively merging clusters. Finally, in this study a classification of all farmers into homogeneous groups with similar decision-making behavior (similar MAUF) is performed.

Data sources and description of studied area: The practical application of the methodology proposed above is based on the Doroudzan Channel in Southern Iran.

This irrigated area covers 68364 ha, on which about 9600 irrigators are farming. The official water allocation is around 13560 m3/ha per year, but on average only 12433 m3/ha per year is actually consumed. The most widely used irrigation system is gravity irrigation. Two kinds of data are needed to feed the models which were obtained from official records and through a survey of farmers.

Farm-level data were collected from a sample of 57 farms located in the Zarghan district in the Doroudzan Basin in the south of Iran was selected by a two-stage cluster sampling during the years 2000/2001-2004/2005. Data were then collected using designed questionnaires. The survey provides detailed information on the production patterns, input use, crop production yields, prices of the inputs and outputs, social and personality characteristics of farmers and structural characteristics during the 5 years of survey.

Descriptive statistics and specifications: Descriptive statistics are provided in Table 1. During the 5 years of the survey distribution of homogenous groups is as follows: 9 farmers in cluster 1, 16 farmers in cluster 2 and 32 farmers in cluster 3. The farms in cluster 1 are larger than farms in both cluster 2 and 3 (169.7, 80 and 18.39 ha on average respectively).

Table 1: Descriptive statistics

	Clusters								
	1			2			3		
Variable	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
No. of farms	9	16	32						
Farm size	139	200	169.7	60	120	80	3	56	18.39
Age of farmers (years)	40	60	51.33	23	59	46	26	67	45.17
Farmer's education (years)	8	12	10.66	5	14	10.5	0	14	4.93
Farmer's experience (years)	20	45	35	4	50	29.75	8	50	25.6
Degree of mechanization (percent of applied machinery)	35	77	66.7	70	90	87.3	35	55	43
Cropping patterns	Wheat, Barley, Carrot, Cabbage, Rice, Corn, Tomato, Onion, Sugar beet			Wheat, Barley, Carrot, Cabbage, Corn, Tomato, Onion, Sugar beet			Wheat, Carrot, Cabbage, Corn, Tomato		

On the basis of the data obtained, it is evident that farmers in cluster 1 are older than farmers in the other clusters, who are in general more educated and have more experience than other clusters counterparts. Where, the average age, education level and experience of farmers in cluster 1, 2 and 3 are 51.33, 10.66 and 35 years, 46, 10.5 and 29.75 years and 45.17, 4.93 and 25.6 years, respectively.

The farmers did 66.7 percent of operations by machinery in cluster 1 whereas; it is 87.3 and 43 percent for farmers in clusters 2 and 3 respectively. With respect to information that presents in Table 1 three groups of farmers are different and results of this study at further sections confirmed it [50-52].

RESULTS AND DISCUSSION

Pay-off matrix: The results obtained for the pay-off matrix for each of clusters are as shown in Tables 2-4. The diagonal elements of the pay-off matrix in these Tables are the optimum values for each individual goal and the corresponding off-diagonal elements are the values of the other objectives evaluated using the basic elements of the optimized solution vector.

Elicitation of the MAUF: The next step is the elicitation of the MAUF for each cluster:

Cluster 1: The farmers in this cluster maximize TGM with a weighting of W_1=90.9% and minimize risk (VAR) with a weighting of W_2=9.1%. Minimization of labor input is not objective taken into account by this group of irrigators (W_3 = 0). When the values that make up the utility function are normalized, we obtain the following expression:

$$MAUF_1 = 69.4\ (TGM) - 0.00000142\ (VAR)$$

Cluster 2: The farmers in this cluster maximize TGM with a weighting of W_1=90.83% and minimize risk (VAR) with a weighting of W_2=9.17%. Minimization of labor input is not objective taken into account by this group of irrigators (W_3 = 0). Using these weights we obtain the following utility function of the farmers grouped in cluster 2:

$$MAUF_2 = 12.45\ (TGM) - 0.0000003587\ (VAR)$$

Cluster 3: The farmers in this cluster maximize TGM with a weighting of W_1=87.43% and minimize risk (VAR) with a weighting of W_2=19.57%. Minimization of labor input is not objective taken into account by this group of irrigators (W_3= 0). As in the two previous cases, minimization of labor is not an objective in these farmers' decision-making. As, the values that make up the utility function are normalized, we obtain the following expression of the behavior of this group of farmers:

$$MAUF_3 = 36.688\ (TGM) - 0.000008475\ (VAR)$$

It is also worth pointing out that for all cases the weighting obtained for the TL attribute was zero. This does not necessarily mean that farmers ignore the objective of maximizing their leisure time and minimizing management complexity. This result of our study is same with result of some studies such as Berbel and Rodriguez, [21]; Go´mez-Limo´n and Riesgo, [31] who believed that indeed, given the lack of conflict between the objective of minimizing risk and that of minimizing total labor, it is possible that the weights assigned to the VAR attribute actually include the importance given by the farmers to both objectives, minimization of VAR and minimization of TL, taken together.

Table 2: Pay-off matrix for cluster 1

	Objective be optimized			
Value obtained	TGM	VAR	TL	Observed
TGM (10^4 RIALS)	152328.5	31126.79	21337.81	143171.1
VAR (10^6 RIALS^2)	$6.46 * 10^8$	4619758	5661210.31	$5.83 * 10^8$
TL (man - day)	14547.24	2500.5	1732.8	13457.34

Table 3: Pay-off matrix for cluster 2

	Objective be optimized			
Value obtained	TGM	VAR	TL	Observed
TGM (10^4 RIALS)	$82801.52 * 10^3$	14372.17	9851.25	76754.9
VAR (10^6 RIALS^2)	$2.57 * 10^8$	984696.14	1206681	$1.96 * 10^8$
TL (man - day)	7854.64	1154.65	830	7240.64

Table 4: Pay-off matrix for cluster 3

	Objective be optimized			
Value obtained	TGM	VAR	TL	Observed
TGM (10^4 RIALS)	27269.98	5149.87	3438.79	24274.58
VAR (10^6 RIALS^2)	14900693	69166.48	221992.2	9609603
TL (man - day)	2299.88	382.04	269.1	2083.91

Table 5: Results of model validation in each clusters

	Cluster 1 (169.7 ha)			Cluster 2 (80 ha)			Cluster 3 (18.39 ha)		
Objectives	Observed value	Predicted value	Deviation (%)	Observed value	Predicted value	Deviation (%)	Observed value	Predicted value	Deviation (%)
TGM (10^4 RIALS)	143171.1	152328.5	-6.4	76754.9	82801.53	-7.9	24274.58	27271.43	-12.34
VAR (10^6 RIALS^2)	5830	7650	-31.21	1960	2570	-31.12	96.096	148.237	-54.42
TL (Work day- man)	13457.34	14547.24	-8.1	7240.64	7783.2	-7.5	2083.91	2288.73	-9.83
Decision variables (ha)	Observed crop mix	Predicted crop mix	Deviation (ha)	Observed crop mix	Predicted crop mix	Deviation (ha)	Observed crop mix	Predicted crop mix	Deviation (ha)
Wheat	40	32.1	7.9	18	20.5	-2.5	9.2	8	1.2
Barley	3	0	3	4	0	4	0	0	0
Rice	4	2.7	1.3	0	0	0	0	0	0
Corn	42	50	-8	22	17.5	4.5	4.8	4.1	0.7
Tomato	5	7	-2	4	5	-1	5	5	0
Onion	5	8	-3	8	8	0	0	0	0
Sugar beet	42	45	-3	15	17.5	-2.5	0	0	0
Carrot	10	10	0	6	8	-2	2.39	3.3	-0.91
Cabbage	10	10	0	7	8	-1	3	4	-1
Divergence index	161	164.8	28.2 (16.6%)	84	84.5	17.5 (21.9%)	24.39	24.4	3.81 (20.7%)

Model validation: Table 5 represents the results of the validation for the different clusters, illustrating the resultant deviations in the objectives and in the decision variables spaces. The results obtained for the divergence index (the sum of all absolute deviations in the variables space) in this Table indicate that the optimum crop mix of each cluster was close enough to actual crop mixes. Therefore, these models are close approximations to the farmers' own decision processes.

Water demand functions: This section analyses the results obtained by the simulations of alternative scenarios. For this purpose we set a base scenario that considered the existence of a water pricing, also measuring it influence on the total demand for water.

Table 6: Water demand in each homogenous groups

	Tariffs for water									
Water demand	Zero	Current rate	2 times	5 times	10 times	15 times	20 times	30 times	50 times	100 times
Cluster 1 (m^3)	2235080	2235080	2235080	2235080	2235080	2235080	2046148	1648400	1159934	320729.2
Cluster 2 (m^3)	1028360	1028360	1028360	1028360	1028360	959660	715000	598500	378521.7	59006.34
Cluster 3 (m^3)	275065.5	275065.5	275065.5	275065.5	275065.5	233419	204116	187262.4	133740.5	14802.2

Table 7: Average water demand in each homogenous groups

	Tariffs for water									
Water demand	Zero	Current rate	2 times	5 times	10 times	15 times	20 times	30 times	50 times	100 times
Cluster 1 (m^3/ha)	13562.3	13562.3	13562.3	13562.3	13562.3	13562.3	12988.1	12238.2	10438.2	3338.3
Cluster 2 (m^3/ha)	12169.9	12169.9	12169.9	12169.9	12169.9	11556.9	10800	10100	8080	1715.2
Cluster 3 (m^3/ha)	11273.2	11273.2	11273.2	11273.2	11273.2	10545	9600	8400	7010	1315.1

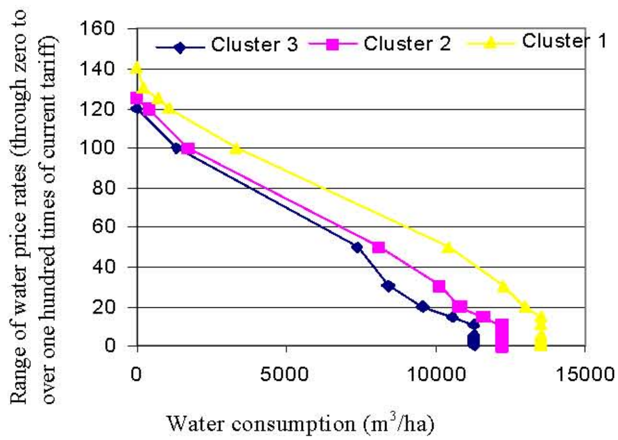

Fig. 1: Irrigation water demand curves

It is simulated a range of prices through zero to one hundred times of current tariff. These simulations give the water demand in each homogenous groups (m^3/ha) and demand curves (Fig. 1) for irrigation water; one for each cluster of farmers considered in the case study area.

Tables 6 and 7 show the influence of mentioned scenarios on total and average water demand in each homogenous groups (m^3/ha) respectively.

The quantity of demand for water varies significantly from cluster to cluster. At the current tariff cluster 1 consumes 13562.3 m^3 per ha, while cluster 2 consumes 12169.9 m^3 per ha. Thus, cluster 1 consumes a substantially higher volume than cluster 2. Cluster 3 has the lowest water consumption, whose water requirements are 11273.17 m^3/ha. Current water consumption by the last two clusters is considerably lower than their endowments (13562.3 m^3/ha). This is due to the risk averse behavior that characterizes both groups of farmers.

Figure 1 indicates that actual behavior patterns vary significantly when specific groups of irrigators are studied. However, as can be observed in our analysis, patterns of consumption vary along the demand curves as a result of increases in the water price.

It can be seen that in the elastic segments of the curves the increase in the price of water produces great savings in consumption due to changes in crop mixes, substitute rain-fed crops and apply deficit irrigation methods while in the inelastic segments, tariff rises do not result in significant water savings, since farmers are not induced to change their crop plans.

The greatest savings are obtained with pricing scenarios in elastic segments of the water demand curves. This is the reason that to produce any significant further saving in the amount of water consumed by farmers. Thus, it would be necessary to apply tariffs higher than threshold price in the elastic segment of water demand curve.

CONCLUSION

Most water management systems are concerned with satisfying conflicting demands of various groups and

MCDM techniques provide a potential mechanism for resolving these conflicts. Therefore, in order to correctly simulate the behavior of farmers it is necessary to consider the different utility functions that they use, within a multi-criteria framework. These techniques provide better results than simple linear programming solutions because they integrate the effect of all the objectives simultaneously. There are an increasing number of highly sophisticated LP solvers that could easily be adapted to solve MCDM problems using Weighted Goal Programming (WGP) as illustrated with the example problem.

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