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Irrigation water pricing: differential impacts on irrigated farms

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Abstract

European water policy, as set out in the Water Framework Directive (WFD), requires all EU Member States to implement volumetric water pricing at rates that roughly cover the total costs of providing water services. The objective of this paper is to develop a methodology that, for the different types of farm in an irrigable area, will enable us to analyse the differential impact that a pricing policy for irrigation water would have. For this purpose, Multi-Attribute Utility Theory (MAUT) mathematical programming models were used. The methodology is implemented on a representative area in the Duero Valley in Spain. Our results show the usefulness of differential analysis in evaluating the impact of a water pricing policy. This allows significant differences in the evolution of agricultural incomes to be observed, as well as the recovery of costs by the State, demand for agricultural employment and the consumption of agrochemicals resulting from rising prices of irrigation water in various groups of farmers within a given irrigated area.

JEL classification: Q25; Q15; C61

Keywords: Irrigation water; Pricing; Water framework directive; Multi-criteria programming; Cluster analysis

1. Introduction and objectives

The constantly rising demand for water in Spain clearly demonstrates the growing relative shortage of this resource. This has motivated an intensive polemic about the efficiency of use of water by irrigated farms, which account for 80% of national water consumption (Ministry of the Environment, 1998). The apparently poor management of water in Spanish irrigated areas (large losses of water and its application to surplus crops, with low profitability and low labour demand) has served as an argument for the implementation of demand water policies as an indispensable solution to this problem. Such demand policies consist in the main of the public re-allocation of water resources, water pricing, the promotion of infrastructure improvements and the introduction of water markets (Chakravorty and Zilberman, 2000; Dinar et al., 1997; Easter and Hearne, 1995; Sumpsi et al., 1998).

The water economy has matured not only in Spain, but is shared by other Member States of the European Union (EU). This situation has caused EU institutions to decide to develop a common policy in the field of water management. One result of this interest has been

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the recent approval of the Directive 2000/60/CE of the European Parliament and of the Council, which established a framework for Community action in the field of water policy (the Water Framework Directive, or WFD). There is no doubt that one of the most divisive topics in the WFD is the article related to water pricing (article 9), that has been proposed as the main policy for dealing with demand for water within the EU.

The WFD establishes the convenience of using water pricing as the economic instrument to achieve the proposed environmental objectives. In this sense, article 9 establishes that "Member States shall take account of the principle of recovery of the costs of water services, including environmental and resource costs". However, article 9 also states that "Member States may in doing so have regards to the social, environmental and economic effects of the recovery as well as the geographic and climatic conditions of the region or regions affected". This final text of article 9 is much less tough than the one proposed in the first drafts of the WFD, which pursued the compulsory implementation of the water full-cost-recovery (FCR) principle. In fact, article 9 as approved only requires the introduction before 2010 of the necessary water pricing measures in order to "provide adequate incentives for users to use water resources efficiently, and thereby contribute to the environmental objectives of this Directive".

Although water pricing is an environmentalist demand, the reasoning on which this instrument is based is purely economic. In this sense, farmers in irrigated areas, according to economic theory, would respond to the introduction of (or an increase in) water prices by reducing their consumption, in accordance with a negatively sloped demand curve. In this way the water savings obtained would be re-distributed among other uses such as productive or environmental purposes (ecological flows in rivers, etc.), according to the preferences of society. Such a reallocation of water resources would improve the efficiency of their use.

However, this set of assumptions, made from the point of view of classical economic theory, has been disputed by various authors who have studied the impact of water pricing on specific irrigated areas. In the case of Spain, these include Varela-Ortega et al. (1998), Gómez-Limón and Berbel (2000) and Feijoó et al. (2000). These studies have all demonstrated that water pricing would not stimulate the desired changes in water use (reduced consumption and re-allocation of the water saved), due to the low elasticity of demand for irrigation water. Furthermore, the implementation of this economic instrument would produce collateral effects, such as a decrease in agricultural income and a reduction in the demand for agricultural labour. These conclusions could be generalised to other countries and regions, both within and outside the EU, where irrigated agriculture is a strategic sector in rural areas.

The above comments show the importance of water pricing policies for the future of irrigation, since presumably they would have a negative influence on its competitiveness, and thus on the rural areas in which it is employed.

We propose a methodology for the analysis of the potential impact of the implementation of water pricing on irrigated agriculture, studying its economic, social and environmental effects. For this purpose, simulation is proposed as a suitable technique for implementing the mathematical programming models developed under the Multi-Criteria Decision Making (MCDM) paradigm. The methodological proposal outlined here is also based on a careful classification (aggregation) of farmers, in order to enable the differential impacts of water pricing by farm-types (homogeneous groups of farmers) to be analysed.

We apply the proposed methodology to a particular irrigated area (Community of Irrigators of the Pisuerga Channel, Spain), analysing the impact of the hypothetical implementation of recovery-of-costs water pricing proposed by the WFD on different groups of farmers.

2. Methodology: key elements

Before the proposed methodology can be discussed, a brief presentation of the elements on which it is based is required: i.e. the classification (aggregation) of farmers into homogeneous groups and the scenarios proposed for the WFD implementation.

2.1. Aggregation bias and cluster analysis

Modelling agricultural systems at any level other than that of the individual farm implies problems of aggregation bias. The introduction of a set of farms in a unique programming model overestimates the mobility of resources among the production units, allowing combinations of resources that are not possible in the real world. The final result of these models is that the value obtained for the objective function is biased upward and the values obtained for decision variables tend to be unachievable in real life (Hazell and Norton, 1986, p. 145).

This aggregation bias can only be avoided if the farms included in the models fulfill strict criteria regarding homogeneity (Day, 1963): technological homogeneity (same possibilities of production, same type of resources, same technological level and same management capacity), pecuniary proportionality (proportional profit expectations for each crop) and institutional proportionality (availability of resources to the individual farm proportional to average availability).

The case studied here is an irrigated area of about 10,000 ha (Community of Irrigators of the Pisuerga Channel). This is a relatively small area that can be regarded as fairly homogeneous in terms of soil quality and climate, and where the same range of crops can be cultivated with similar yields. Furthermore, the whole set of farms that are integrated in this agricultural system operates the same technology at a similar level of mechanization. Given these conditions, it can be assumed that the requirements regarding technological homogeneity and pecuniary proportionality are basically fulfilled.

Given efficient capital and labour markets, the constraints included in modelling this system have been limited to agronomic requirements (crop rotations) and the restrictions imposed by the Common Agricultural Policy (land set-aside and sugar-beet quotas) that are similar for all farms. The requirement of institutional proportionality may thus also be regarded as having been met.

We thus conclude that the agricultural systems in question can be modelled by means of a unique linear program with relatively small problems of aggregation bias. Numerous studies with similar units of analysis have been based on this kind of aggregate model, e.g. Bernard et al. (1988), Chaudhry and Young (1989), Kulshreshtha and Tewari (1991), Varela-Ortega et al. (1998), Berbel and Gómez-Limón (2000).

However, it is essential to note that the requirements discussed above are based on the assumption that the sole criterion on which decisions are based is profit maximisation. If a multi-criteria perspective is being considered, an additional homogeneity requirement emerges in order to avoid aggregation bias; viz., homogeneity related to choice criteria. This kind of similarity has been implicitly assumed in studies based on a unique multi-criteria model for the whole set of farmers in the area being analysed (for example, Gómez-Limón and Berbel, 2000).

Nevertheless, we suspect that the decision criteria of farmer homogeneity does not reflect the normal situation in real agricultural systems. This suspicion, as will be commented, has been confirmed by a survey of the area analysed. In fact, the decision criteria are primarily based on psychological characteristics of the decision-makers, which differ significantly from farmer to farmer. According to this perspective, the differences in decision-making (crop mix) among farmers in the same production area must be primarily due to differences in their objective functions (in which the weightings given to different criteria are condensed), rather than other differences related to the profits of economic activities or disparities in resources requirements or endowments.

In order to avoid aggregation bias resulting from lumping together farmers with significantly different objective functions, a classification of all farmers into homogeneous groups with similar decision-making behaviour (objective functions) is required. For this issue we have taken the work of Berbel and Rodríguez (1998) as a starting point. These authors noted that for this type of classification the most efficient method is cluster analysis, taking farmers' real decision-making vectors (actual crop mix) as the classification criterion.

The term 'cluster analysis' embraces a loosely structured body of algorithms, which are used in the exploration of data from the measurement of a number of characteristics for a collection of observations. Cluster analysis is concerned with the discovery of groups. The word 'cluster' or 'group' should be interpreted as a collection of 'similar' objects. In our case, the objects are farmers operating in a particular irrigated area, randomly sampled (34 producers).

In order to obtain homogeneous groups with similar decision-making behaviour, the cluster analysis should be performed using the relative importance of the different management criteria regarded by farmers as classification variables. Unfortunately, as shown by Berbel and Rodríguez (1998), these data, obtained through verbal questioning, only poorly represent the real weightings that are taken into account by farmers.

This may be because management criteria are not well understood by farmers. Deffontaines and Petit (1985) claim that farmers' criteria are better observed by indirect methods than by direct questioning. Thus, the sample of farmers needs to be grouped according to variables that can be regarded as proxies for the relative importance of management criteria.

We assume 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, labour or water availability. Thus, the surface (in percentage) devoted to the different crops (proxies of the real criteria) are used as classification variables to group farmers using the cluster technique.

Note that the homogeneous groups obtained in this way can be regarded as 'fixed' in the short and medium terms. As noted above, the decision criteria are based on psychological features of the decision-makers, which is why they may be regarded as producers' structural characteristics. These psychological features, and thus the criteria, are unlikely to change in the near future. This means that the selection variables chosen allow farmers to be grouped into clusters that are robust to changes in the policy framework (i.e. water pricing). In other words, 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.

Clustering was performed using the Chi-squared distance among actual crop mixes, expressed in percentages, and the Ward method (minimum variance). For more detailed information about this statistical technique, see Chatfield and Collins (1980) or Hair et al. (1998).

2.2. Implementation of the WFD. Scenario proposals

Spanish irrigation water users currently pay the State a price that only partially reflects the cost of providing water. In fact, only the operational and management costs are covered by this tariff. The remaining financial costs (i.e. capital depreciation) are met by the national budget and form a hidden subsidy to users, especially in the agricultural sector.

The first practical problem that we encountered in establishing appropriate scenarios is the lack of information regarding the real cost of irrigation water that should be used by each member state to implement the WFD. As far as Spain is concerned, only a few studies have been carried out, giving results that range from 0.01 to 0.11 €/m^3. In addition to the difficulty of setting up a reliable cost estimate for irrigation in practice, this wide range of costs is due to the different levels of analysis (basin, smaller hydrological system or a single irrigated area) used for this purpose and the kinds of costs considered (see for example Massaruto, 2002).

We therefore selected three water pricing scenarios for our case study:

- *'Subsidised' price*. This considers a price of 0.02 €/m^3. This price will not be capable, in our opinion, of recovering total costs, but might at least serve as an economic instrument to encourage more efficient resource use.
- *'Medium' price*. A price of 0.04 €/m^3 may be regarded as a 'fair' value for cost recovery, that would at least cover the financial costs.
- *'FCR' price*. A price of 0.06 €/m^3 would be a tough application of full-cost-recovery principle, including a provision for environmental costs.

3. Methodology

3.1. Methodology diagram

The methodology adopted is displayed graphically in Fig. 1.According to this plan, the proposed methodology can be divided into four principal stages, as outlined below:The first stage is the classification of farmers performed using cluster analysis and explained above.

Once homogeneous groups of farmers have been defined, the second stage builds the mathematical models. For each cluster a different multi-criteria model is developed in order to allow independent simulations based on the decision-making behaviour of the various groups of farmers to be run. For this purpose, the basic elements of any mathematical model; i.e. decision variables, objective function and set of constraints, have to be outlined. While the choice of crop

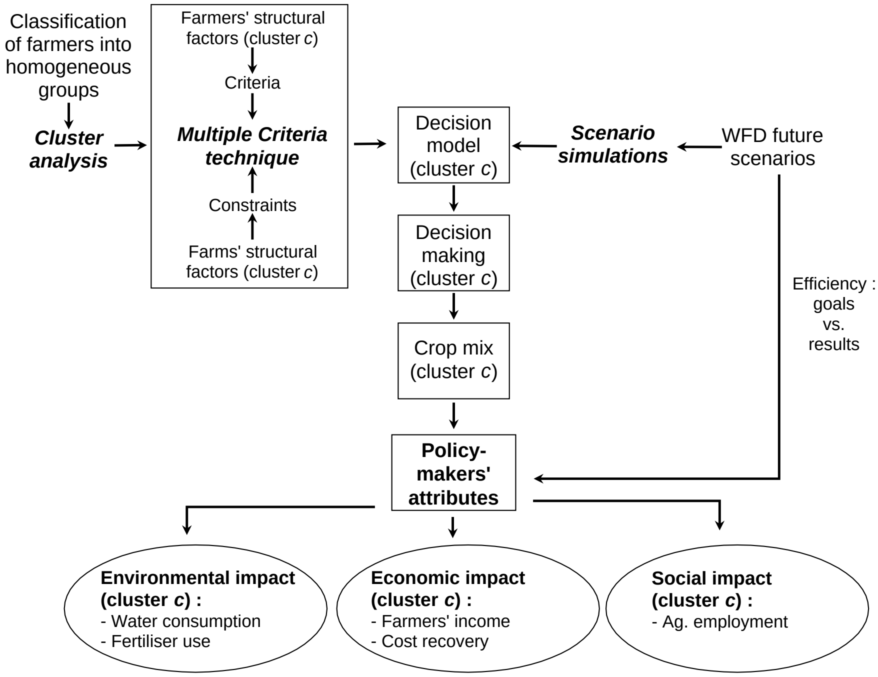

Fig. 1. Research methodology.

areas as a decision variable does not cause any problem (observing crop diversity in the area studied is sufficient), the objective function and constraints require more detailed analysis. The objective function for each cluster is estimated using a multi-criteria procedure as described in the next section and data gathered for the current situation (highly subsidised water price per unit of irrigated surface). Again, the estimated objective functions are assumed to be those that the farmers in each cluster will attempt to maximise in the future, under any policy scenario that they might face.

The constraints that need to be satisfied in the decision-making process are mainly due to the structural characteristics of the farms (climate, soil fertility, market limits, CAP requirements, etc.), that are basically identical for all. Only slight differences have been fixed by clusters according to the data obtained in the survey; these are mainly related to farm-type area and sugar-beet quotas.

The third stage of the study performs the simulations. Thus, based on the WFD implementation scenarios outlined above, the decisions taken, i.e. crop mixes, by the different clusters of irrigators were obtained.

The crop mixes obtained from the models are of little significance for agricultural and environmental policy-makers, who are primarily interested in a series of attributes that result from these crop mixes. These include economic attributes (farmers' income and the state's recovery of costs), social attributes (direct employment generated in the agricultural sector) and environmental attributes (water consumption and fertiliser consumption). The calculation of these attributes and the analysis of the efficiency of the economic instrument (water pricing) proposed will be the core of the fourth stage of our methodology.

3.2. Multi-criteria programming approach

As opposed to the classical approach, we have assumed that not only profit determines the level of farmer's utility, but that other attributes such as risk, leisure time, management complexity, etc. are also involved in farmers' decision-making. For discussions of MCDM techniques in agriculture see Anderson et al. (1977), Hazell and Norton (1986), Romero and Rehman (1989), and Hardaker et al. (1997).

Given evidence on how farmers take decisions while trying to simultaneously optimise a range of conflicting objectives, we propose Multi-Attribute Utility Theory (MAUT) as the theoretical framework for the MCDM programming to be implemented. MAUT, particularly as developed by Keeney and Raiffa (1976), has often been argued to have the soundest theoretical structure of all multi-criteria techniques (Ballestero and Romero, 1998). At the same time, from a practical point of view, the elicitation of utility functions has presented many difficulties. In this paper, we adopt a methodology that overcomes these limitations.

The aim of MAUT is to reduce a decision problem with multiple criteria to a cardinal function that ranks alternatives according to a single criterion. Thus, the utilities of n attributes from different alternatives are captured in a quantitative way via a utility function, mathematically, $U = U(x_1, x_2, \ldots, x_n)$, where U is the Multi-Attribute Utility Function (MAUF) and x_i are the attributes regarded by the decision-maker as relevant in the decision-making process.

If the attributes are mutually utility-independent[1] the formulation becomes $U = f\{u_1(x_1), u_2(x_2), \ldots, u_n(x_n)\}$ and takes either the additive form:

$$U(x_1, x_2, \ldots, x_n) = \Sigma w_i u_i(x_i), \quad i = 1, 2, \ldots, n \tag{1}$$

or multiplicative form:

$$U(x_1, x_2, \ldots, x_n) = \frac{\left\{\prod(K w_i u_i(x_i) + 1) - 1\right\}}{K}, \quad i = 1, 2, \ldots, n, \tag{2}$$

where $0 \leq w_i \leq 1$ and $K = f(w_i)$. If the attributes are mutually utility-independent and $\Sigma w_i = 1$, then $K = 0$, and the utility function is additive. If $\Sigma w_i \neq 1$, then $K \neq 0$, and the mathematical form is multiplicative (Keeney, 1974; Keeney and Raiffa, 1976; Fishburn, 1982).

Both of these forms have been elicited on the basis of expected utility theory through the use of techniques that involve the choice made by the decision-maker between a certain outcome and a lottery (Anderson et al., 1977; Biswas, 1997; Hardaker et al., 1997). 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. Mathematically, the expression (1) in its simple form becomes:

$$U_j = \sum_{i=1}^{n} w_i u_i(r_j), \quad i = 1, \ldots, m, \tag{3}$$

where U_j 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.

Considering an additive MAUF, alternatives are ranked by adding contributions from each attribute. Since attributes are measured in terms of different units, normalisation is required to enable them to be added. The weighting of each attribute expresses its relative importance.

Although the additive utility function represents a simplification of the true utility function, Edwards (1977), Farmer (1987), Huirne and Hardaker (1998) and Amador et al. (1998) have shown that the additive function yields extremely close approximations to the hypothetical true function even when the conditions of utility independence (Fishburn, 1982; Hardaker et al., 1997) are not satisfied.[2] As Hwang and Yoon (1981, p. 103) 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". Given this justification for the use of the additive utility function, we take the further step of assuming that the individual attribute utility functions are linear. Hence, the expression (3) becomes:

$$U_j = \sum_{i=1}^{n} w_i r_{ij}, \quad i = 1, \ldots, m, \tag{4}$$

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

This formulation implies linear utility-indifference curves (constant partial marginal utility), a rather

[1] "An attribute x_i is utility independent of the other $n - 1$ attributes x_j if preferences for lotteries involving different levels of attribute x_i do not depend on the levels of the other $n - 1$ attributes x_j" (Huirne and Hardaker, 1998).

[2] The approximation of the additive formulation to the real multiattribute function, supported by several empirical studies, is explained by some authors on the basis of psychological reasons (Dawes and Corrigan, 1974; Einhorn and Hogart, 1975; Dawes, 1979).

strong assumption that can be regarded as an approximation if the attributes vary within a narrow range (Edwards, 1977; Hardaker et al., 1997, p. 165). There is some evidence for this hypothesis in agriculture. Thus, Huirne and Hardaker (1998) show that the slope of the single-attribute utility function has little impact on the ranking of alternatives. Likewise, Amador et al. (1998) analyse how linear and quasi-concave functions yield almost the same results. We therefore adopt this simplification in the elicitation of the additive utility function.

3.3. MAUF elicitation technique

To estimate the relative weightings w_i we select a methodology that avoids the necessity of interacting directly with farmers, and in which the utility function is elicited on the basis of the revealed preferences implicit in the real values of decision variables (i.e. the actual crop mix). The methodology adopted for the estimation of the additive MAUFs is based on the technique proposed by Sumpsi et al. (1997) and extended by Amador et al. (1998). It is based upon weighted goal programming and has previously been used by Berbel and Rodríguez (1998), Gómez-Limón and Berbel (2000), Arriaza et al. (2002) and Gómez-Limón et al. (2002). To avoid unnecessary repetition, we refer to these papers for details of all aspects of this multi-criteria technique. Here, we wish only to point out that the results obtained by this technique are the weights (w_i) that imply utility functions that are capable of reproducing farmers' observed behaviour. As Dyer (1977) demonstrates, these weights are consistent with the following separable and additive utility functions:

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

where k_i is a normalising factor.

Precisely because this utility surrogate needs to fulfil the requirements of being an additive MAUF, it must range between 0 and 1. For this reason, the following equivalent MAUF expression is used,

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

The normalising factor in (6) is thus the difference between the maximum (f_i^*) and minimum (f_{i*}) values for objective i in the pay-off matrix developed for the criteria considered.

3.4. Scenario simulations

In order to simulate the impacts of the various pricing scenarios we estimate different water-demand functions in the case study area; one for each cluster. These demand curves are the result of the irrigators' short-term production adjustments in the face of rising irrigation water prices. For this reason, the simulation modelled the following alternatives:

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

Although the implementation of water stressing (deficit irrigation) is also a way of dealing with higher water tariffs, it is not considered since it is not a real alternative for farmers, as was shown by the survey. When the price of irrigation water is raised, farmers will opt for less water-intensive or simply rain-fed crops in preference to implementing deficit irrigation. Identical responses have been found in other empirical studies (Sunding et al., 1997; Schuck and Green, 2001). This behaviour is mainly the result of the low elasticity of irrigation water production functions (Nieswiadomy, 1988; Ogg and Gollehon, 1989). The introduction of water-conservation techniques (e.g. improvements in irrigation infrastructure or new technologies) is not considered, since this would go beyond the short-term horizon of this study.

Generating demand curves in accordance with the above considerations required corresponding simulation models to be built. These models are similar to those that enabled us to obtain the pay-off matrices, but they take the following considerations into account:

1. The objective functions (to be maximised) were the utility functions obtained for each cluster.
2. In calculating the gross margin of each crop (GM_i), the water cost generated by the different tariffs has been included. The gross margins considered are thus equal to the initial gross margins (with zero volumetric tariff) less the amount paid for water

(water consumption for each crop multiplied by the tariffs) for each water price.
3. New activities (crops) are introduced in order to permit the modelling of rain-fed crops.

Once the models have been built, the method of simulating farmers' behaviour as a reaction to the water pricing policy consists of parametrising the water price, starting with a tariff of 0 €/m^3. This tariff is increased progressively, being incorporated as a variable cost for the different crops according to their respective water needs. For each tariff it is possible to determine the crop mixes that would be planned by farmers, which enables us to calculate water consumption (demand curve for irrigation water) and the values of other attributes of interest to the analyst, as is demonstrated in the next section.

3.5. Policy-makers' attributes

The attributes are values of interest to the analyst that are deduced from the vectors of decision variables (crop plans) chosen by the agricultural producers. The models were developed in order to derive from farmers' the crop plans, the values of attributes that are of interest to policy-makers. These attributes are:

- *Economic impacts*. These impacts are measured in our model by the gross margin (farm revenue estimator) and by the public-sector revenue derived from irrigation water payments, both measured in €/ha.
- *Social impact*. Agriculture is the main source of employment in most irrigated areas in continental Spain. Hence, changes in irrigation water pricing policy could affect the social structure of these regions. This phenomenon can be evaluated via the labour demand attribute, which is measured in Agricultural Labour Units (ALU) per ha.
- *Environmental impact*. Estimated water consumption provides an indication of the amount of water saved in agriculture as a result of the implementation of the WFD. Another environmental effect of growing relevance is the non-source pollution caused by the use of agrochemicals in agriculture. Because of this, the consumption of nitrogen fertilisers (measured in nitrogen fertilisers units—NFU—per ha) is taken as an indicator of the environmental impact of agricultural activities that could be modified by the WFD pricing policy.

4. Case study

4.1. Description of area

The practical application of the methodology proposed above is based on the Community of Irrigators of the Pisuerga Channel in Northern Spain.

This irrigated area covers 9392 ha, on which about 1000 irrigators are farming. The range of crops in 2000, a typical year, included winter cereals such as wheat and barley (50.6%), alfalfa (17.6%), sugar-beet (16.2%), maize (8.3%), sunflower (2.5%) and other minor crops (4.7%).

The official water allocation is around 8100 m^3/ha per year, but on average only 7000 m^3/ha per year is actually consumed. The most widely used irrigation system is gravity irrigation, while sprinkler irrigation is used only for sugar-beet and alfalfa. Water pricing is currently based on a fixed sum per unit of irrigated surface, like most irrigated areas in Spain. In this case the water tariff is 60.59 €/ha, equivalent to a volumetric tariff of 0.010 €/m^3.

The selection of this agricultural system as the case study is due to its specific characteristics, in that it can be regarded as an 'average' irrigated area in the Duero basin. Other practical reasons, such as the availability of good-quality data, were also taken into account. The data needed to feed the models were obtained from official records and through a survey of farmers.

4.2. Cluster analysis

Following the cluster technique proposed in Section 2.1, the first result obtained in our case study is the dendrogram chart, shown in Fig. 2.

Based on Fig. 2 we chose to cut the tree by the horizontal line indicated, leaving us with three homogeneous groups of farmers. These clusters are characterised as follows:

- *Cluster 1*. The first group includes the largest percentage of farmers (44.1%), who farm 34.5% of the area under study. These farmers are younger than those of the other clusters (average 46 years

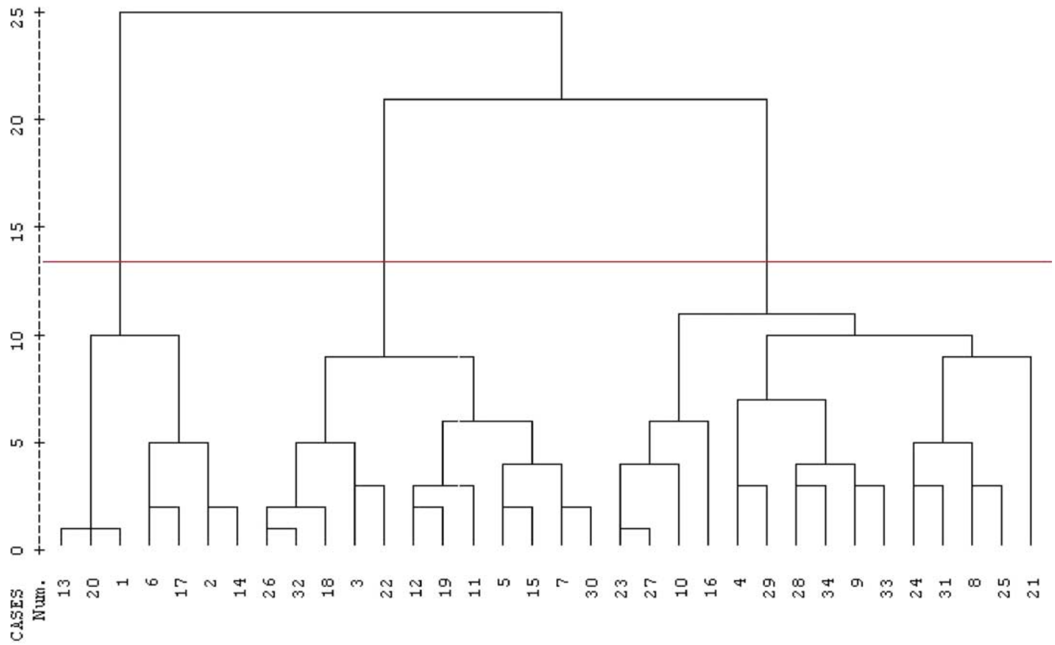

Fig. 2. Cluster dendrogram.

of age), and agriculture is their principal activity. They manage medium-size farms (27.8 ha on average), mostly sown with alfalfa (36%), sugar beet (20%) and maize (20%). These are the most lucrative crops the farmers can choose, but also the most risky. This feature leads us to label this group as 'commercial farmers'.

- *Cluster 2*. The second group consists of 35.3% of the farmers, who farm the largest proportion of the irrigated area (51.9%). It includes mature farmers (51 years old on average), with large irrigated farms (50.5 ha) which are run on a full-time basis. Their land is mostly planted to winter cereals (40%), which are less profitable but less risky than other crops, and to maize and sugar beet (which together covered 42% of the total area). We label these 'large conservative farmers'.
- *Cluster 3*. The third group has the smallest proportion of farmers (20.6%) and also represents the smallest proportion of the irrigated area (13.7%). This cluster has a similar age profile to that of cluster 2, with small irrigated farms (23.7 ha), whose farmers, unlike the other groups, are not exclusively engaged in agriculture. The crop mix mainly consists of winter cereals (65%) and alfalfa (25%). These features led us to label this group 'part-time conservative farmers'.

4.3. Multi-criteria modelling

The main elements of the model are described in the following.

4.3.1. Decision variables

Each cluster of farmers has a set of variables X_i (crops). These are the decision variables that may assume any value that forms part of the feasible set (see Appendix A).

4.3.2. Objectives

After a survey of the study area, we conclude that farmers choose a crop distribution that takes the following objectives into account:

- *Maximisation of total gross margin* (TGM), as a proxy for short run profit. TGM is obtained from the average crop gross margins from a time series of 7 years (1993/1994 to 1999/2000) in constant 2000 euros.
- *Minimisation of risk* (VAR). Risk is an important factor in agricultural production. Farmers have a

marked aversion to risk, so the model should include this objective. In this case risk was measured as the variance of the TGM (VAR), following the classical Markowitz (1952) approach. The risk is thus computed as $\vec{X}'\cdot[\text{cov}]\cdot\vec{X}$, where [cov] is the variance-covariance matrix of the crop gross margins during the seven-year period, and $\vec{X}$ is the crop decision vector.

- *Minimisation of total labour input* (TL). This objective implies not only a reduction in the cost of this input but also an increase in leisure time and a reduction in managerial involvement (labour-intensive crops require more technical supervision).
- *Minimisation of working capital* (K). This has the aim of reducing the level of indebtedness. In order to model this objective we divided the year into months, differentiating in this way the periods of cropping activities (capital immobilisation) and sales (income).

The mathematical definition of these objectives and their implementation in the programming models is outlined in Appendix A.

These objectives, which are selected a priori, were analysed for the different clusters in accordance with the methodology described above. This analysis enables us to assess the importance of each objective in the decision-making process for each homogeneous group of farmers. While TGM, VAR, TL and K are the most relevant arguments in the MAUFs as revealed through the questionnaire, additional attributes might be able to explain the real behaviour of farmers more accurately.[3] We assume that MAUFs that include the attributes proposed above are adequate to model farmers' decision-making processes, giving better results than assuming profit maximisation behaviour through the classic PL and its variants.

4.3.3. Constraints

We identify the following constraints within the model as applied to each group of farmers:

(a) *Land constraint*. The sum of all crops must be equal to the total surface available to the farm type of each cluster.
(b) *CAP constraints*. We include 5% set-aside for cereal, oilseed and protein crops (COPs). Sugar beet, because of the quota, is limited in each cluster to the maximum hectareage in the period studied.
(c) *Rotational constraints*. These were taken into account according to the criteria revealed for the farmers in the survey.
(d) *Market constraints*. We decided to limit alfalfa hectareage to the maximum in the period 1993-97 because of its rigid demand. This crop is exclusively consumed by the regional flocks of dairy cows and sheep, whose sizes are fairly constant, due to CAP quotas, making it unlikely that alfalfa production sold could be higher than the maximum proposed.

4.3.4. Modelling by clusters

The basic model described above was built separately for each of the clusters defined above. In these models the objectives considered a priori were the same for all groups of farmers. However, the constraints were altered depending on the clusters analysed, taking their particular circumstances into account. For example, for cluster 1 the available farm-land was 27.97 ha, for cluster 2 it was 52.54 ha, etc. The same applies to the sugar-beet quota and market limitations. Appendix A describes the model for cluster 1, in order to clarify the procedure followed.

5. Results

5.1. Objective weighting and utility function elicitation

Once the basic models are built for each cluster, they are optimised successively for the individual objectives proposed: TGM maximisation and VAR, TL and K minimisation, thus obtaining the pay-off matrices for each group of farmers. The results of the pay-off matrix for cluster 1 can be seen in Appendix B.

The next step is to identify the objectives that participate in the decision-making process and the degree to which they are taken into account by each

[3] The questionnaire included the criteria most often considered in the literature on multi-criteria modelling of farmers' decisions. However, it did not included other hypothetical objectives that are difficult to model through mathematical programming (primarily psychological variables), although they could be involved in the real MAUFs.

homogeneous group of farmers. For this purpose, the multi-criteria technique proposed in Section 3.3 (Sumpsi et al., 1997) was employed for every cluster. An example of the development of this technique can be found in Appendix B.

The final result of this step is the elicitation of the MAUF for each cluster:

Cluster 1: Commercial farmers. The farmers in this cluster maximise TGM with a weighting of 52.9% (W_1) and minimise risk (VAR) with a weighting of 47.1% (W_2). Minimisation of labour input and of working capital (K) are not objectives taken into account by this group of irrigators ($W_3 = W_4 = 0$). Using these weights we obtain the following utility function surrogate, defining the behaviour of the farmers grouped in cluster 1:

$$U = 23.9\,\mathrm{TGM} - 0.0133\,\mathrm{VAR} \tag{7}$$

Cluster 2: Large conservative farmers. The farmers in this cluster maximise their TGM with a weighting of 29.9% (W_1) and minimise the risk (VAR) with a weighting of 70.1% (W_2). As with cluster 1 minimisation of working capital and of labour are not taken into account by this group ($W_3 = W_4 = 0$). When the values that make up the utility function are normalised, we obtain the following expression:

$$U = 87.6\,\mathrm{TGM} - 0.0032\,\mathrm{VAR} \tag{8}$$

Cluster 3: Part-time conservative farmers. For the group, the resolution of the multi-criteria technique provides the following objective weights: TGM maximisation is given a weight of 12.8% (W_1), risk (VAR) minimisation 78.1% (W_2), and working capital (K) minimisation, 9.1% (W_4). As in the two previous cases, minimisation of labour is not an objective in these farmers' decision-making ($W_3 = 0$). Normalising the utility function results in the following surrogate expression of the behaviour of this group of farmers:

$$U = 72.7\,\mathrm{TGM} - 0.142\,\mathrm{VAR} - 70.4\,K \tag{9}$$

5.2. Model validation

Validation of the models built for each group of farmers is a key aspect of testing the quality of the results. The procedure employed was to compare the real situation (observed) with the data simulated by the models for the current scenario. This type of comparison is the most common method of validating models (Qureshi et al., 1999). Table 1 summarises the validation for the different clusters, illustrating the resultant deviations in the objectives and in the decision variables spaces.

Although there is no limit or threshold value to validate models, the results obtained for the divergence index (the sum of all absolute deviations in the vari-

Table 1
Validation

Objectives	Cluster 1 (27.97 ha)			Cluster 2 (52.54 ha)			Cluster 3 (23.70 ha)		
	Observed value	Predicted values	Deviation (%)	Observed value	Predicted values	Deviation (%)	Observed value	Predicted values	Deviation (%)
TGM (€)	28,502	28,286	0.8	42,120	43,006	−2.1	18,250	16,429	10.0
VAR (10^3 €^{2})	229.09	262.70	−14.7	843.19	876.80	−4.0	92.96	73.86	20.6
TL (h)	2,021	1,729	14.5	2,903	2,522	13.1	1,328	1,265	4.8
K (€)	12,979	10,377	20.0	35,335	33,444	5.4	4,259	3,734	12.3
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)
Winter cereals	5.54	6.40	−0.86	18.17	21.42	−3.25	15.49	14.27	1.22
Maize	5.46	6.59	−1.13	8.62	7.75	0.87	0.00	0.00	0.00
Sugar beet	5.58	4.52	1.05	16.71	16.91	−0.20	1.86	1.87	−0.01
Sunflower	0.40	0.00	0.40	2.58	0.00	2.58	0.00	1.30	−1.30
Alfalfa	10.16	9.62	0.54	2.08	2.08	0.00	6.00	4.60	1.40
Set-aside	0.83	0.83	0.00	4.37	4.37	0.00	0.36	1.67	−1.31
Divergence index	27.97	27.97	3.98 (14%)	52.53	52.53	6.90 (13%)	23.71	23.71	5.24 (22%)

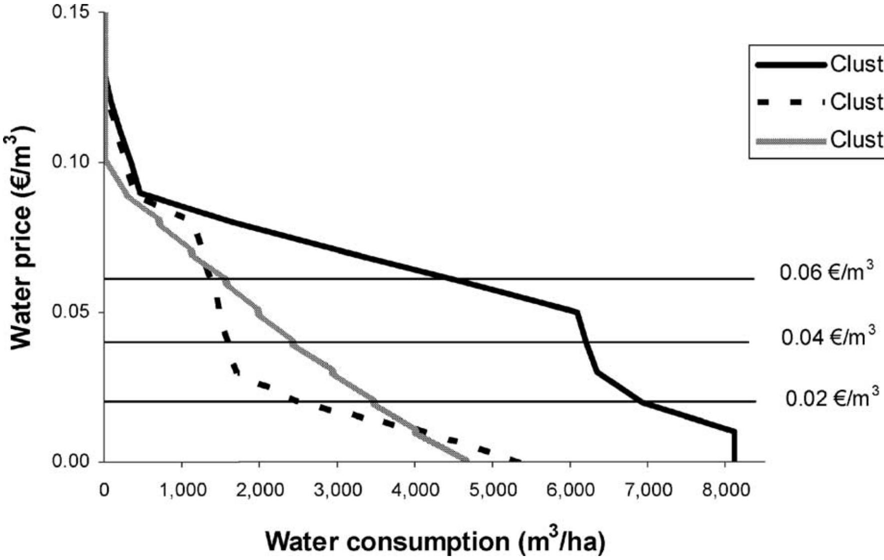

Fig. 3. Irrigation water demand curves.

ables space) in Table 1 indicate that the optimum crop mix of each cluster was close enough to actual mixes to suggest that the models are good approximations to the farmers' own decision processes.

5.3. Water demand functions

The simulations described above (Section 3.4) give us the demand curves for irrigation water; one for each cluster of farmers considered in the case study area (Fig. 3).

The quantity of water demanded varies significantly from cluster to cluster, thus, at the current tariff (zero marginal cost, price $= 0$ €/m^3), cluster 1 consumes 8105 m^3 per ha, a substantially higher volume than cluster 2, whose water requirements are 5360 m^3/ha. Cluster 3 has the lowest water consumption, close to 4600 m^3/ha. Current water consumption by the last two clusters is considerably lower than their endowments (8105 m^3/ha). This is due to the risk averse behaviour that characterises both groups of farmers. Their crop plans thus emphasise 'safe' crops (with smaller TGM variability) with smaller water requirements, such as winter cereals.

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. The water demand curves demonstrate the behaviour patterns displayed by farmers in each of the three clusters. Until now, most analyses of demand curves have aggregated all farmers, implementing a single model for the whole set of farmers operating in the study area. Examples of such studies include those of Wahl (1989), Montginoul and Rieu (1996), Varela-Ortega et al. (1998) and Gómez-Limón and Berbel (2000). These works demonstrate a common pattern for water demand curves, characterised by an inelastic segment for low irrigation water prices, followed by an elastic interval for higher prices. However, as can be observed in our analysis, actual behaviour patterns vary significantly when specific groups of irrigators (clusters with homogeneous decision criteria) are studied. 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.

We simulate a range of prices between 0.02 €/m^3 and 0.06 €/m^3, which we believe approximates likely

Table 2
Water consumption reductions (m^3/ha)

	Subsidised price 0.02 €/m^3	Medium price 0.04 €/m^3	FCR price 0.06 €/m^3
Cluster 1 (current consumption = 8,105)	1,192 (14.7%)	1,896 (23.4%)	3,504 (43.2%)
Cluster 2 (current consumption = 5,360)	2,794 (52.1%)	3,752 (70.0%)	3,965 (74.0%)
Cluster 3 (current consumption = 3,659)	1,176 (25.2%)	2,227 (47.8%)	3,082 (66.2%)

Reduction in water consumption as a percentage of current demand for water shown in parentheses.

future pricing scenarios for the implementation of the WFD. Table 2 shows the influence of these scenarios on agricultural water consumption in our case study area.

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. For example, in the case of cluster 2, the implementation of the 'medium' price results in similar water savings as the 'FCR' price (70 and 74%, respectively). This is due to the existence of a relatively inelastic segment in the demand curve at tariffs lower than 0.08 €/m^3, where the rigidity of the crop plan and its water requirements is evident. To produce any significant further saving in the amount of water consumed by this group of farmers it would be necessary to apply tariffs higher than this threshold price.

The overall effects of water pricing policy on the water saved by all clusters are significant. The implementation of a tariff equal to 0.06 €/m^3 generates reductions in water use of 74 and 66%, respectively, in clusters 2 and 3 compared with current consumption.

As can be seen, the most important relative savings take place in the more conservative groups. This is explained by the different degree of utility contributed by water resources to each group of irrigators. In the case of cluster 1, which is characterised primarily by profit maximising behaviour, the marginal utility of water use is very close to its marginal productivity. Hence, this group's usage resembles the predictions of classical economic theory, i.e. using a resource until its marginal productivity approaches its price. However, in the case of the farmers who assign great importance to risk aversion (clusters 2 and 3), water's marginal utility is much lower than its marginal productivity. For farmers in both clusters, water, besides productivity, generates 'disutilities', as a higher rate of consumption (for more water-intensive crops) is associated with higher risk and a greater demand for working capital. Thus, as the price of water rises, its respective marginal utility for the most conservative producers diminishes more rapidly than for the commercial farmers (cluster 1).

5.4. Economic impact

The changes in gross margins motivated by the implementation of the WFD and the public revenues ob-

Table 3
Reductions in gross margins reductions and public revenues (€/ha)

	Subsidised price 0.02 €/m^3		Medium price 0.04 €/m^3		FCR price 0.06 €/m^3	
	TGM decrease	Public revenues	TGM decrease	Public revenues	TGM decrease	Public revenues
Cluster 1 (current TGM = 963)	−182 (−18.8%)	138	−339 (−35.2%)	248	−517 (−53.7%)	365
Cluster 2 (current TGM = 610)	−147 (−24.0%)	51	−210 (−34.4%)	64	−259 (−42.5%)	84
Cluster 3 (current TGM = 619)	−137 (−22.1%)	70	−246 (−39.7%)	97	−317 (−51.3%)	95

Reduction in gross margin as a percentage of current gross margins.

tained by the different pricing levels can be seen in Table 3.

Generally speaking, a water pricing policy would lead to a significant reduction in farmers' incomes. These losses have two causes. First, the payment of water tariffs to the State, and second, the withdrawal of crops with higher water demands (corn, sugar beet or alfalfa), that usually generate greater profits. This can be observed in Table 3, where only a proportion of the fall in TGM is transferred via water pricing to the State, while the remaining losses are due to changes in crop plans. The greatest losses of income are produced by the highest tariff considered (0.06 €/m^3). These maximum losses in gross margins range between 42.5 and 53.7% of the current TGM, depending on the cluster. This fact might produce a significant drop in agricultural competitiveness. In any case, it is necessary to emphasise that the effect on agricultural incomes would be quite similar in the three clusters considered. This decrease in the profitability of irrigated agriculture might well lead in the medium term to the economic unsustainability of farms, which in turn might bring about the withdrawal of a large percentage of farmers from agriculture.

5.5. Social impact

Besides a reduction in water consumption, a rise in the price of water would lead to a decrease in the employment directly generated by the agricultural sector, as shown in Table 4.

The decrease in agricultural employment is a social impact caused by substitution of the most water-intensive crops, which are normally also more labour-intensive, by others with reduced water and labour requirements.

These decreases in agricultural employment could exceed 20% of current labour demand (cluster 2 for 'FCR' price), which could have a serious social impact in the area studied. However, this drop in input demand should not be dramatised because farms in the study area are basically family operations, with little hired personnel. Thus, this drop in demand for labour would basically be translated into an increase in farmers' leisure. Note that the decrease in agricultural employment caused by the implementation of irrigation water pricing would be smaller in the case of cluster 1 than for the most conservative groups. This is due to the more market-oriented behaviour of this group of farmers (higher weighting of the TGM objective in the MAUF) which, as pointed out above, makes these producers value water much more than the farmers in clusters 2 and 3. This is why they would be more reluctant to decrease their water consumption—or the associated the demand for labour—in the face of successive tariff increments.

5.6. Environmental impact

The introduction of irrigation water pricing would also reduce nitrogen fertiliser consumption, as shown in Table 4. This is due to the relationship between current crop plans and the demand for nitrogen fertilisers. Crops such as maize and sugar beet (with high water requirements) have higher requirements for this kind of fertilisation than others with lower irrigation needs, such as irrigated winter cereals, and much more than rain-fed crops.

Table 4
Changes in employment (ALU/ha) and consumption of nitrogen fertilisers (NFU/ha)

	Subsidised price 0.02 €/m^3		Medium price 0.04 €/m^3		FCR price 0.06 €/m^3	
	Employment	Nitrogen	Employment	Nitrogen	Employment	Nitrogen
Cluster 1 (current TL = 71.1) (current NFU = 68.7)	−2.7 (−3.8%)	−20 (−28.6%)	−5.5 (−7.8%)	−24 (−34.8%)	−12.1 (−16.9%)	−22 (−32.3%)
Cluster 2 (current TL = 46.8) (current NFU = 120.7)	−6.5 (−13.9%)	−39 (−32.6%)	−9.2 (−19.6%)	−56 (−46.5%)	−10.9 (−23.3%)	−61 (−50.2%)
Cluster 3 (current TL = 48.7) (current NFU = 38.6)	−3.2 (−6.5%)	−6 (−16.4%)	−6.5 (−13.3%)	−7 (−18.4%)	−9.4 (−19.4%)	−8 (−19.6%)

Percentage reduction in employment relative to current demand for labour and percentage reduction in nitrogen fertiliser consumption vis-à-vis the current situation.

As mentioned above with respect to other policy-makers' attributes, the elasticity of demand will influence the achievement of the environmental objectives (e.g. a decrease in the consumption of nitrogen fertilisers) proposed. The greatest changes in crop mixes would occur in the elastic segments, where pricing policy would be most efficient.

5.7. *Differential approach versus aggregated demand*

Having explained the methodology employed and analysed the most important results of the case study, we finally consider whether considering disaggregated demands explains actual water consumption better than the traditional aggregated approach. We therefore estimate the whole demand curve for the case study area as a weighted addition of the disaggregated demands already obtained ('Disaggregated' line in Fig. 4) and compare it with demand curves estimated (i) through considering a unique aggregated model with a profit maximisation objective function ('Profit max' line in Fig. 4), and (ii) an aggregated MAUF objective function obtained for the irrigated area as a whole ('Aggregated' line in Fig. 4).

To compare the different demand estimation approaches, the only objective data we have is the actual average consumption in this irrigated area, which is around 7000 m^3/ha. Since current water tariffs are paid as a fixed sum per unit of irrigated area, we can regard the actual volumetric price as equal to 0 €/m^3. As seen in Fig. 4, the disaggregated approach provides the best approximation to actual water consumption. For tariffs higher than 0 €/m^3 we have no information about consumption, but experience suggests that the disaggregated demand method employed in this paper is more reliable, since it indicates lower consumption at low prices, as is likely to be true, and because it is smoother than the other two curves. We conclude that the disaggregated approach proposed here is a useful means of providing more accurate estimates of farmers' responses in the face of new policies, such as water pricing in this case.

6. Concluding remarks

The conclusions derived from the methodology employed in this paper can be summarised in terms of two fundamental points. First, it is remarkable how irrigated areas, despite being highly homogeneous in terms of soil, climate, market and technological conditions, show great heterogeneity in the responses of their farmers. In fact, farmers in these areas show a great variability in the management criteria that they use to plan their crop mixes. This fact makes it necessary to utilise differential modelling for the different groups of farmers in the areas under study, in order to minimise the problems of bias produced by fully ag-

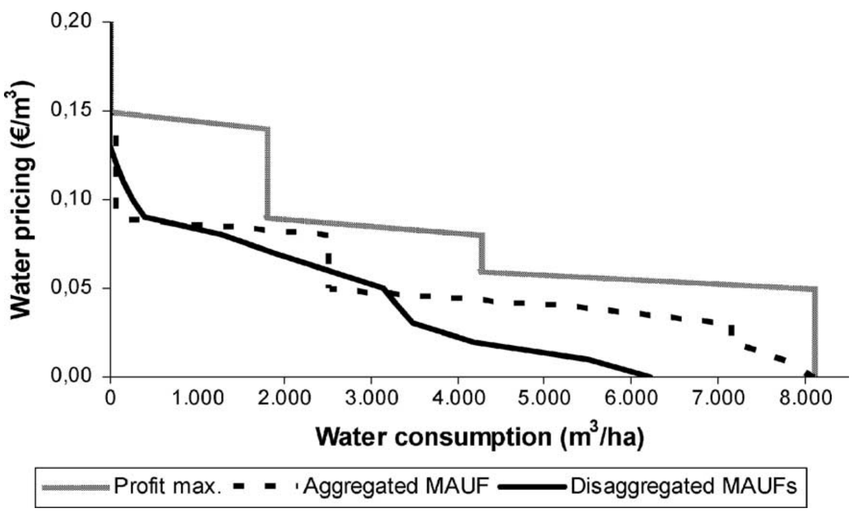

Fig. 4. Water demand curves for the whole irrigated area.

gregated models. This requires irrigators to be classified into homogeneous groups, for example by means of a clustering technique.

Second, the different types of productive behaviour of the groups defined by the cluster technique can be synthesized by estimating additive MAUFs. Thus, on the basis of actual production decisions, we can estimate the different objective weightings for each cluster of farmers in order to generate their respective utility surrogate formulations. These functions are employed as objective functions in the simulation models. In this sense we consider that a methodology based on the MAUT can be a valuable technique for simulating the differentiated behaviour of groups of farmers who are faced with the implementation of water pricing policies.

The practical application of the methodology proposed was done in an area of the Duero basin, which is typical of the continental agriculture practised in central Spain. On the basis of these results, we may conclude that the analysis of water pricing policy impacts clearly demonstrates that farmers display different behaviour patterns related to this natural resource. This diversity is shown by the different shapes of the demand curves for each of the clusters considered. The effects of irrigation water pricing thus vary significantly depending on the group of farmers being considered.

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Appendix A. Basic multi-criteria model definition. The case of cluster 1

Variables[a]	X_1 wheat	X_2 barley	X_3 maize	X_4 sugar-beet	X_5 sunflower	X_6 alfalfa	X_7 set-aside	WC1	WC2	WC3	...	WC11	WC12	K		
GM	390	511	960	1,336	393	1,301	160									
VAR[b]																
TL	19.60	19.60	33.30	66.70	19.60	50.00	2.90									
K (see maximin programming below)																
Constraints																
Land	1	1	1	1	1	1	1								=	27.97
CAP 1 (max. set-aside)	0.20	0.20	0.20		0.20		−1								≥	0.00
CAP 2 (min. set-aside)							1								≥	0.83
CAP 3 (quota)				1											≤	5.51
Rotation 1	1	1													≤	13.85
Rotation 2			1												≤	13.85
Rotation 3				1											≤	13.85
Rotation 4					1										≤	13.85
Rotation 5 (multi-year crop)						1									≤	9.62
Market						1									≤	10.52
Maximin programming for working capital (K)																
Working capital 1	0	0	0	−6.36	0	0	0	1					−1		≥	0.00
Working capital 2	0	0	0	−229.64	0	0	0	−1	1						≥	0.00
Working capital 3	−82.39	−24.34	−138.99	−356.65	0	0	0		−1	1					≥	0.00
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮			⋮	⋮	⋮			⋮	⋮
Working capital 11	−254.01	−96.45	−50.10	0	−9.01	0	−37.30					1			≥	0.00
Working capital 12	0	−105.89	732.79	3321.67	0	0	211.21					−1	1		≥	0.00
Maximin 1								1						−1	≤	0.00
Maximin 2									1					−1	≤	0.00
⋮										⋮	⋮	⋮		⋮	⋮	⋮
Maximin 12													1	−1	≤	0.00

[a] The variables X_2 (rain-fed wheat), X_4 (rain-fed barley) and X_{10} (rain-fed sunflowers) are not included in this 'basic' model, which was built to determine the pay-off matrix. These crops are included in the scenario simulations (see Section 3.4).

[b] (VAR) $= \vec{X}_i{}^t\,[\mathrm{cov}]\,\vec{X}_i$, where [cov]. For more detail see the following Table 5.

Table 5
Variance–covariance matrix for cluster 1

$$[\mathrm{cov}] = \begin{vmatrix} 11222.05 & 13673.55 & 29502.96 & 25170.96 & 4793.99 & 6463.65 \\ 13673.55 & 24840.45 & 44029.25 & 44653.81 & 8638.59 & 9712.39 \\ 29502.96 & 44029.25 & 277421.36 & 31449.69 & 44485.98 & 51057.45 \\ 25170.96 & 44653.81 & 31449.69 & 179675.35 & 11968.68 & 14852.03 \\ 4793.99 & 8638.59 & 44485.98 & 11968.68 & 13911.35 & 4879.24 \\ 6463.65 & 9712.39 & 51057.45 & 14852.03 & 4879.24 & 42345.56 \end{vmatrix}$$

Appendix B. Methodological procedure for objective weighting and elicitation of MAUFs. The case of cluster 1

The methodology used for MAUF elicitation was developed by Sumpsi et al. (1997) and extended by Amador et al. (1998). It is based upon weighted goal programming and has previously been used by Berbel and Rodríguez (1998), Gómez-Limón and Berbel (2000), Arriaza et al. (2002) and Gómez-Limón et al. (2002). This method may be summarised as follows:

1. Each attribute is defined as a mathematical function f_i of decision variables × (crop area). These attributes are proposed a priori as the most relevant decision criteria utilised by farmers. As explained in Section 4.3, the $f_i(x)$ considered in our case were TGM, VAR, TL and K.
2. The pay-off matrix is calculated, where f_{ij} is the value of the ith objective when the jth objective is optimised. The main diagonal is the 'ideal' point defined by the individually obtained optimum. In the case of cluster 1 the results obtained for the pay-off matrix are as shown in Table 6.

   Attached to the above matrix a column has been included to indicate the values achieved for the different objectives in the real world for this cluster. These data are now used to estimate objective weights.
3. The following $q+1$ system of equations is solved;

$$\sum_{i=1}^{q} w_i f_{ij} = f_i, \quad i = 1, 2, \dots, q \quad \text{and}$$
$$\sum_{i=1}^{q} w_i = 1, \tag{B.1}$$

   where q is the number of a priori relevant objectives, w_i are the weights attached to each objective, f_{ij} are the elements of the pay-off matrix and f_i the real values reached in the observed behaviour of farmers.
4. Normally, there is not an exact solution to system (1) and it is therefore necessary to solve a problem by minimising the sum of deviational variables that find the closest set of weights;

$$\mathrm{Min} \sum_{i=1}^{q} \frac{n_i + p_i}{f_i} \quad \text{subject to :}$$

$$\sum_{i=1}^{q} w_i f_{ij} + n_i - p_i = f_i, \quad i = 1, 2, \dots, q \quad \text{and}$$
$$\sum_{i=1}^{q} w_i = 1, \tag{B.2}$$

   where n_i and p_i are negative and positive deviations, respectively.

Table 6
Payoff matrix for cluster 1 (27.97 ha)

Value obtained	Objective to be optimised				Observed value
	TGM	VAR	TL	K	
GM (euros)	32,357	11,081	10,043	22,261	28,502
VAR (10^3 euros^2)	405.05	31.71	33.24	86.61	229.09
TL (h)	2,133	1,343	1,297	1,706	2,022
K (euros)	16,687	5,864	6,071	1,003	12,979

In the case of cluster 1, the constraints of this mathematical programming are:

$$W_1 \cdot 32,357.09 + W_2 \cdot 11,080.77 + W_3 \cdot 10,042.89 + W_4 \cdot 22,261.43 + n_1 - p_1 = 28,502.46$$
$$W_1 \cdot 405.05 + W_2 \cdot 31.71 + W_3 \cdot 33.24 + W_4 \cdot 86.61 + n_2 - p_2 = 229.09$$
$$W_1 \cdot 2,132.60 + W_2 \cdot 1,343.63 + W_3 \cdot 1,296.79 + W_4 \cdot 1,705.64 + n_3 - p_3 = 2,021.67$$
$$W_1 \cdot 16,686.75 + W_2 \cdot 5,864.25 + W_3 \cdot 6,071.07 + W_4 \cdot 1,002.96 + n_4 - p_4 = 12,978.59$$
$$W_1 + W_2 + W_3 + W_4 = 1$$

The results of solving these equations are the weights:

$$W_1 = 0.529 \qquad W_2 = 0.471 \qquad W_3 = 0 \qquad W_4 = 0$$

As pointed out in Section 3.3, these weights can be used to built a MAUF adjusted to the expression;

$$U = \sum_{i=1}^{n} w_i \frac{f_i(x) - f_{i*}}{f_i{}^* - f_{i*}}, \tag{B.3}$$

where f_i^* is the maximum value for objective i in the pay-off matrix developed for the criteria considered and f_{i*} is the minimum value. Thus, in the example case, the final result of the elicitation process is the algebraic MAUF:

$$\begin{aligned}\mathrm{MAUF}_{\text{cluster 1}} &= 0.529\frac{\mathrm{TGM} - 10,042.89}{32,357.09 - 10,042.89} \\ &\quad + 0.471\frac{40,505,193.01 - \mathrm{VAR}}{40,505,193.01 - 3,170,775.22} \\ &\quad + 0\frac{2132.60 - \mathrm{TL}}{2132.60 - 1296.79} + 0\frac{16,686.75 - K}{16,686.75 - 1002.96}\end{aligned} \tag{B.4}$$

Simplifying this expression in order to obtain the objective function to be maximised in the simulation models, we obtain:

$$\mathrm{MAUF}_{\text{cluster 1}} = 23.9\mathrm{TGM} - 0.0133\mathrm{VAR} \tag{B.5}$$

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