Evaluating Irrigation Water Demand *

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1. Introduction

Irrigation is a high-volume user of water.[1] Irrigated agriculture accounts for a large proportion of water use, especially in many water-scarce areas. Imbalances between water needs and resources are likely to induce conflicts between different categories of users (rural, urban, industrial and other users). In these situations, as water becomes scarce,[2] policymakers attempt to induce farmers to reduce water consumption by implementing economic tools such as quotas or water pricing. Recent reforms on water policies have been implemented (cf. Dinar, 2000) to make farmers increasingly responsible for water conservation. The final result would lead to force all water users to pay the water at its value. Under scarcity, understanding the influence of water price on water-concerned activity is a key contribution to policy analysis. This knowledge, which is the starting point to define water pricing, is inherent to the estimation of the water demand.

As in most other regions and countries, farmers in France are charged for water. The fees are fixed at low levels and do not make farmers responsible for the costs they impose on water supplies. Moreover the knowledge of farmers water consumption remains unprecise. In this context, estimating farmers water demand is difficult and several questions are still unanswered.

There is an important literature assessing how farmers react to changes in the price of water using either econometric models or programming models. These two approaches on irrigation water demand estimation use different techniques, different data and lead to various results.

1.1. Statistical Estimation of Derived Demand for Irrigation Water

Irrigation water demand estimates relying on actual farmer behavior are usally based on cross-sectional water use data (Ogg and Gollehon, 1989). These estimations have commonly used dual input demand specifications (Moore and Negri,

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1992; Moore et al., 1994a, 1994b; Hassine and Thomas, 1997). They represent farmers as a multicrop production firm taking decisions concerning crop choices, crop-level allocations of land in a long-run setting, and water use quantities in the short-run. These studies suggest that water irrigations are unresponsive to change in prices. The inelasticity of irrigation water demand provided by econometric models may be due to the lack of data on crop-level water use. Moreover these works do not use an acreage-based model or a fixed allocatable input model of water use that could better explain short-run decisions.

1.2. Derived Demands from Programming Model

The absence of observations on water consumptions has induced the use of mathematical programming approaches for the estimation of the derived demand for water. Demand estimates have been derived from '*shadow prices*' obtained by computer simulations of profit maximizing behavior. Many of these programming studies use linear programming (Shunway, 1973) or quadratic programming (Howitt et al., 1980). Irrigation demand curve estimates were found to be significatively elastic. These approaches conclude that irrigation water demand is completely inelastic below a threshold price, and elastic beyond (Montginoul and Rieu, 1996; Garrido et al., 1997; Varela-Ortega et al., 1998; Iglesias et al., 1998).

The programming method studies are based on the following scheme. For a given price, one estimates the quantity of water maximizing the farmer's profit. Variations in water prices induce different levels of optimal water quantities. The authors use these informations directly to represent the derived demand for irrigation water. Several assumptions are made concerning the crop yield response function to irrigation water. A major critic is that these pre-specified functions may not precisely represent the biological and physical process of plant growth. Another drawback is that these models ignore the impact of multiple applications of the water for each crop and give more emphasis on crop pattern shifts.

This chapter aims at proposing a methodology to estimate irrigation water demand using programming methods. Our approach is however different from the existing works and is based on the evaluation of the farmer's value for water. Since markets for water do not exist in France it is not simple to determine this value. The first difference with the existing works concerns the definition of the farmer's value for water. We define it as the maximum amount of money the farmer would be willing to pay for the use of the resource. Another major difference concerns the production function used in the estimation. Inhere, we do not specify that function and use a crop-growth simulation model, which gives precise results concerning water-yield relations.

The procedure we propose is a two-stage method composed of a model of farmer behavior description and optimization, followed by an estimation procedure, the latter being chosed to be nonparametric here. First, using a primal optimization approach as modeling framework, we describe the program of the farmer. This one must allocate a limited water supply over an irrigation season in order to maximize his profit evaluated at the harvesting of the crop. We propose a numerical method for obtaining solutions to this problem based on an optimization algorithm. This algorithm integrates the agronomic model, EPIC-PHASE[3] (Cabelguenne and Debaeke, 1995), an economic model, and an algorithm of search of the optimum. This numerical procedure is used for different weather conditions, and for several total water quantities available for irrigation. It generates a database composed of levels of quotas and the associated maximized profits. Second, using this database and nonparametric methods, we estimate the maximized profit functions. The irrigation water demand functions are also estimated by a nonparametric derivation procedure.

This methodology is applied to estimate water irrigation demand in the South-western of France. Our results show that the irrigation water demand functions are decreasing, nonlinear, and strongly depend on weather conditions. These functions can be decomposed into several areas. Irrigation water demand is inelastic for low water prices; and becomes more elastic as prices increase. The price levels at which the changes in responsiveness to prices appear depend on climates and vary around 0.30 F/m^3 for wet weather conditions up to roughly 1.60 F/m^3 for a dry year. These informations are a decisive contribution for defining water pricing policies when water scarcity becomes a leading issue.

The chapter is structured in the following manner. Section 2 describes the methodology for evaluating irrigation water demand function. First, we describe the theoritical method for calculating demand functions; second, the numerical approach to estimate irrigation water demand is presented. Section 3 develops the empirical specification of the model used to estimate a specific regional-dependent water demand and reports the empirical results. We conclude in Section 4.

2. Methodology

2.1. Demand Function Calculations

The calculations of the water demand of the farmer are based on the evaluation of the farmer's value for water under water scarcity. The water demand functions are derived from the dynamic model of the farmer's decisions.

2.1.1. *Analytical Model*

Consider a farmer facing a sequential decision problem of irrigation scheduling on a calendar $1, \dots, T$ with $T - 1$ decision dates. At date 1, the farmer knows the water quota available for the season, Q, the initial water stock in soil, $\bar{V}$, and the state of crop biomass, $\bar{M}$. At each decision date, the farmer has to irrigate,[4] using a quantity of water denoted q_t.

The dynamics of the three state variables respectively are the following: for $t = 1, \dots, T-1$,

$$M_{t+1} - M_t = f_t(M_t, V_t), \quad (1)$$

$$V_{t+1} - V_t = g_t(M_t, V_t, q_t), \quad (2)$$

$$Q_{t+1} - Q_t = -q_t. \quad (3)$$

The change in the level of the biomass at any date (Equation (2)) is a function (f_t) of current date biomass and water stock in soil. The change in water stock in soil (Equation (3)) depends on the same state variables and on the decision taken at the current date. The quota has a simple decreasing dynamic (Equation (3)).

There exists technical constraint on irrigation represented by the following equation:

$$\underline{q} \leq q_t \leq \bar{q} \quad \text{for} \quad q_t > 0. \quad (4)$$

The final date $(t = T)$ corresponds to harvesting when actual crop yield becomes known. Let $Y(\cdot)$ denote the crop yield function; that quantity depends only on the final biomass at date T and is denoted $Y(M_T)$.

The profit per hectare of the farmer can be written as:

$$\Pi = r \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F), \quad (5)$$

where r denotes output price; C_{FT} denotes fixed production costs; c is water price; δ_t is a dummy variable taking the value 1 if the farmer irrigates and 0 if not. C_F represents fixed costs; these costs appear since the farmer is facing labour and energy costs for each watering.

The farmer sequential problem is the following:

$$\underset{\{q_t\}_{t=1,\dots,T-1}}{\text{Max}} \quad r \cdot Y(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t + \delta_t \cdot C_F) \quad (6)$$

$$\text{s/c} \quad \begin{cases} M_{t+1} - M_t = f_t(M_t, V_t), \\ V_{t+1} - V_t = g_t(M_t, V_t, q_t), \end{cases} \quad (7)$$

$$\text{and s/c} \quad \begin{cases} Q_{t+1} - Q_t = -q_t, \\ \delta_t = \begin{cases} 0 & \text{if} \quad q_t = 0, \\ 1 & \text{if} \quad q_t > 0, \end{cases} \\ \underline{q} \leq q_t \leq \bar{q} \quad \text{for} \quad q_t > 0, \\ M_t \geq 0, \quad V_t \geq 0, \quad Q_t \geq 0, \\ M_1 = \bar{M}, \quad V_1 = \bar{V}, \quad Q_1 = Q. \end{cases} \quad (8)$$

The constraints (7) are the main dynamics while (8) are technical, and physical constraints. This problem is purely analytical here and the functions f_t and g_t are unknown. We will however solve it in the next section using an agronomical simulation tool and an optimization procedure.

The solution of this program is the optimal sequence of decisions:

$$q^*(Q) = \{q_t^*\}_{t=1,\dots,T-1}. \tag{9}$$

This sequence strongly depends on the quantity of water available for irrigation, Q.

Using (9) and (5), we obtain the optimized profit function depending on Q as follows:

$$\Pi^*(Q) = r \cdot Y^*(M_T) - C_{FT} - \sum_{t=1}^{T-1} (c \cdot q_t^*(Q) + \delta_t^* \cdot C_F). \tag{10}$$

2.1.2. *Definition of the Value of Water*

Under limited water supply, the value of water as an economic good is the amount of money the farmer is willing to pay for it. Like any other good, water will be used by farmers as long as the benefits from the use of an additional unit of ressource exceed its cost. As water becomes scarce, the farmer value of water becomes greater than the real water price. In other words, the marginal profit $\mathrm{d}\pi/\mathrm{d}Q$ is greater than the water charge c and therefore the farmer is willing to consume more water.

For a given Q, we define the '*water value*' as the maximum amount of money the farmer would be ready to pay for the use of one additionnal unit of the ressource. This 'opportunity' cost, noted $\lambda(Q)$, is defined as the derivative of the optimized profit function:

$$\lambda(Q) = \frac{\mathrm{d}\Pi^*(Q)}{dQ} \tag{11}$$

evaluated for the given quota.

The knowledge of $\lambda(Q)$ for any value of the quota Q gives the '*willingness to pay*' function of the farmer. This function, usually noted $p(Q)$, is the inverse of the '*irrigation water derived demand*' function, noted by $Q(p)$ where p is the irrigation water pricing. Therefore, the irrigation water derived demand function is completely determined once its inverse, the willingness to pay is known.

2.2. Demand Function Estimation

In order to estimate demand function, initially it is necessary to have data relating to quotas and associated maximized profits, and secondly to define an estimation procedure.

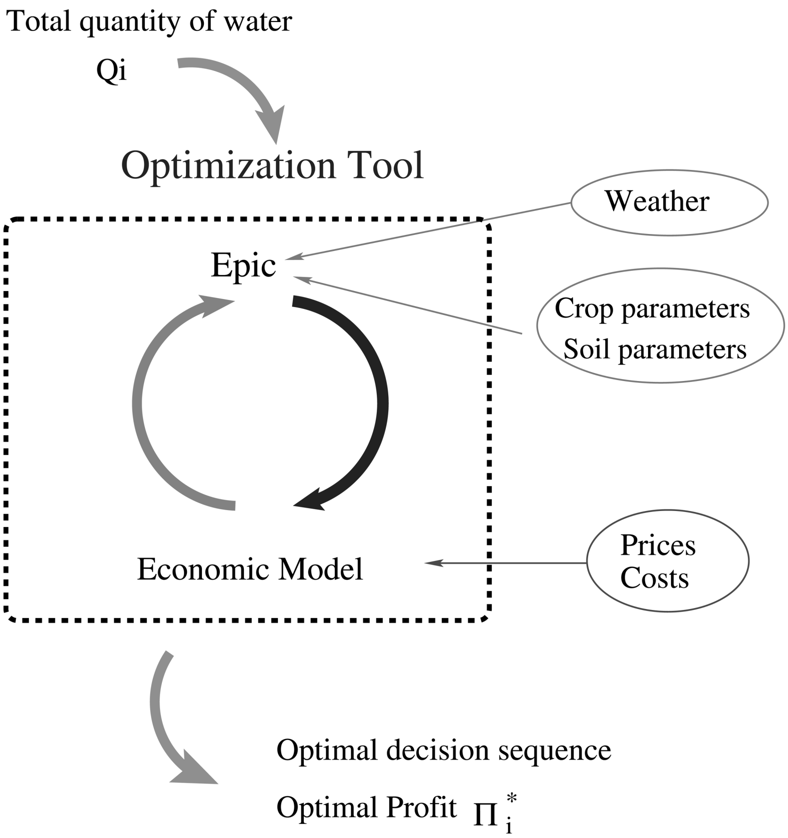

Figure 1. Numerical procedure of resolution.

2.2.1. *Data Generation*

We generate data composed of maximized profits and quotas by solving the sequential decision model described in Section 2.1.1. We will present only a brief description of numerical resolution procedure of this problem here; a detailed description of the sequential decision model can be found in Bontemps and Couture (2001) or Couture (2000a).

Figure 1 shows the numerical procedure integrating the agronomical model, EPIC-PHASE, an economic model, and an algorithm of search of the solution. To simplify the presentation of the numerical framework, we consider the case of known weather conditions and for a given quota. The agronomical model, EPIC-PHASE, was used to generate informations relative to the state variables (previously represented by the transition functions f_t and g_t), and to determine crop yield for various irrigation schedules. Given the prices of inputs and output, the economic model uses the yield predictions from the plant-growth simulation model, and evaluates the profit for each decision sequence. Finally the algorithm of search identifies the optimal decision path by examining exhaustively the set of all simulated profits.[5] Then the maximized profit, Π^*, is obtained. By repeating this procedure for different levels of quotas and then for different weather conditions, we obtain a database on which we base our estimation procedure.

2.2.2. *Nonparametric Estimation*

In order to estimate the water value, it is necessary to estimate first the optimized profit function and its derivative. We chosed a widely used nonparametric kernel estimator (Pagan and Ullah, 1999), to estimate profit function and demand function. A major advantage of nonparametric method is that it allows to estimate an unknown function without assuming its form. Estimation is only based on observed data and is very powerful. In the past decades several nonparametric estimators have been developed (Härdle, 1990), they are all based on a weighted sum of functions of the data.

• *Profit function estimation*

Using (10), the estimation of the optimized profit function lies on the set of simulated data $(Q_i, \Pi_i^*)_{i=1,\dots,n}$ obtained by the numerical model. The unknown function, $\Pi^*(\cdot)$, is ponctually estimated on these n couples (Q_i, Π_i^*). The kernel estimator of profit function evaluated for any value of Q, is a weighted sum of the observed responses Q_i, the weight being a continuous function of observed quantities, Q_i, and evaluation point Q. It is defined as:

$$\widehat{\pi^*(Q)} = \frac{\sum_{i=1}^{n} \Pi_i^* \cdot K\left(\frac{Q_i - Q}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{Q_i - Q}{h}\right)} \quad \forall\, Q \in R, \tag{12}$$

where $K(\cdot)$ is a kernel function, continuously differentiable. We use a Gaussian kernel function among existing kernel functions.[6] Note that $\widehat{\pi^*(Q)}$ will inherit all the continuity and differentiability properties of K. Therefore $\widehat{\pi^*(Q)}$ is continuous and differentiable. The bandwidth, noted h, determines the degree of smoothness of $\widehat{\pi^*(Q)}$; its choice will be discussed latter in this section.

• *Demand function estimation*

In order to estimate the demand function, we will use the property that the profit function estimator is differentiable. If the estimate $\widehat{\pi^*(Q)}$ properly reflects the profit function, $\Pi^*(Q)$, then the estimate of the profit function derivative is equal to the derivative of the estimate of the profit function (Härdle, 1990). Therefore a derivation of (12) with respect to Q will give an estimator of the demand function.[7]

In other words, the estimator $\widehat{\partial\pi^*}/\partial Q(\cdot)$ of $\partial\Pi^*/\partial Q(\cdot)$ is just the derivative of the estimator $\widehat{\pi^*(\cdot)}$. More precisely:

$$\frac{\widehat{\partial\pi^*}}{\partial Q}(Q) = \frac{\partial}{\partial Q}\left(\frac{\sum_{i=1}^{n} \Pi_i^* \cdot K\left(\frac{Q_i - Q}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{Q_i - Q}{h}\right)}\right) \quad \forall\, Q \in R. \tag{13}$$

This can be rewritten as:

$$\begin{aligned}\frac{\widehat{\partial\pi^*}}{\partial Q}(Q) \;=\; & \frac{1}{\left(\sum_{i=1}^{n} K\left(\frac{Q_i - Q}{h}\right)\right)^2} \\ & \cdot \left(-\left(\sum_{i=1}^{n} \Pi_i^* \cdot \frac{1}{h} \cdot K'\left(\frac{Q_i - Q}{h}\right)\right) \cdot \left(\sum_{i=1}^{n} K\left(\frac{Q_i - Q}{h}\right)\right)\right. \\ & \left. + \left(\sum_{i=1}^{n} \Pi_i^* \cdot K\left(\frac{Q_i - Q}{h}\right)\right) \cdot \left(\sum_{i=1}^{n} \frac{1}{h} \cdot K'\left(\frac{Q_i - Q}{h}\right)\right)\right).\end{aligned}$$

The estimator $\widehat{\partial\pi^*}/\partial Q(Q)$ is also continuously differentiable because it incorporates the kernel function $K(\cdot)$ and its derivative $K'(\cdot)$.

• *Smoothing parameter selection*

Choosing the bandwidth, h, is always a crucial problem. If h is small, then we get an interpolation of the data. On the other hand, if h is high, then the estimator is a constant function that assigns the sample mean to each point. There exist several approaches to bandwidth selection (Vieu, 1993) using theorical considerations (*plug-in method*) or based-data method (*cross-validation method*).

A feature of these approaches is that the selected bandwidth is not fully adapted, particularly if the number of observations is small. We use as a benchmark the value obtained by cross-validation. The aim of this method is to choose a value for h minimizing the cross-validation criterion, defined as a sum of distances between the estimator $\widehat{\pi}^*(\cdot)$ evaluated at Q_i and the real data observed Π_i^*. We denote the bandwidth selected by the cross-validation criterion by h^*. In practice, a refinement consists in using a slightly smaller bandwidth than h^* in order to limit oversmoothing.

Following Härdle (1990), the smoothing parameter selected for demand function estimator is the same that the one choosed for profit function estimator, even if this argument may be discussed.

Table 1. ■■Caption?■■. Source: ITCF (1998); Michalland (1995) and Couture (2000a).

Year	Output price r (Francs/Tonne)	Water price c (Francs/m^3)	Fixed Cost per irrigation C_F (Francs)	Fixed cost C_{FT} (Francs)
1989	1049	0.25	150	2150
1991	1038	0.25	150	2150
1993	778	0.25	150	2150

3. An Application in the South-West of France

The procedure for demand function determination was applied using data prevailing in the area of the South-West of France. In this area, agriculture is the largest water consumer with 2/3 of total water consumption. During low river flow periods there is a strong competition on water with urban and industrial uses. In this area, irrigated agriculture is quite recent and concerns a large part of crops such as corn. Irrigation needs depend strongly on weather conditions. Irrigation water was drawn from rivers supplied by mountain reservoirs. The irrigation tools used in the South-West of France are generally sprinkler systems. The reference crop is corn because it remains the main irrigated crop in this area.

3.1. Data

A first set of data is required by the crop growth simulator model. This data set includes weather, soil, technical and irrigation practices, and crop data. The daily weather input file was developed from data collected at the INRA station in Toulouse, for a 14-year series (1983–1996). The soil caracteristic data were included in the crop growth model. The soil is clayey and chalky.

Economic output and input price data are included as a secondary data set, see Table 1. Output prices are farm-level producer prices. Input prices include irrigation variable costs and fixed costs by watering, and other fixed production costs. The fixed cost, (C_F), per irrigation includes energy and labour costs. The fixed production costs, (C_{FT}), are composed of fertilizer, nitrate, seed, and hail insurance costs.

3.2. Estimation Results

We have allowed the quota of available water for irrigation to vary[8] between 0 and 4500 m^3 per hectare. In order to account for weather variability, we have run the model over 14 years available, but we have restricted our attention for three climates : a '*dry*' year (1989), a '*medium*' year (1991) and a '*wet*' year (1993).

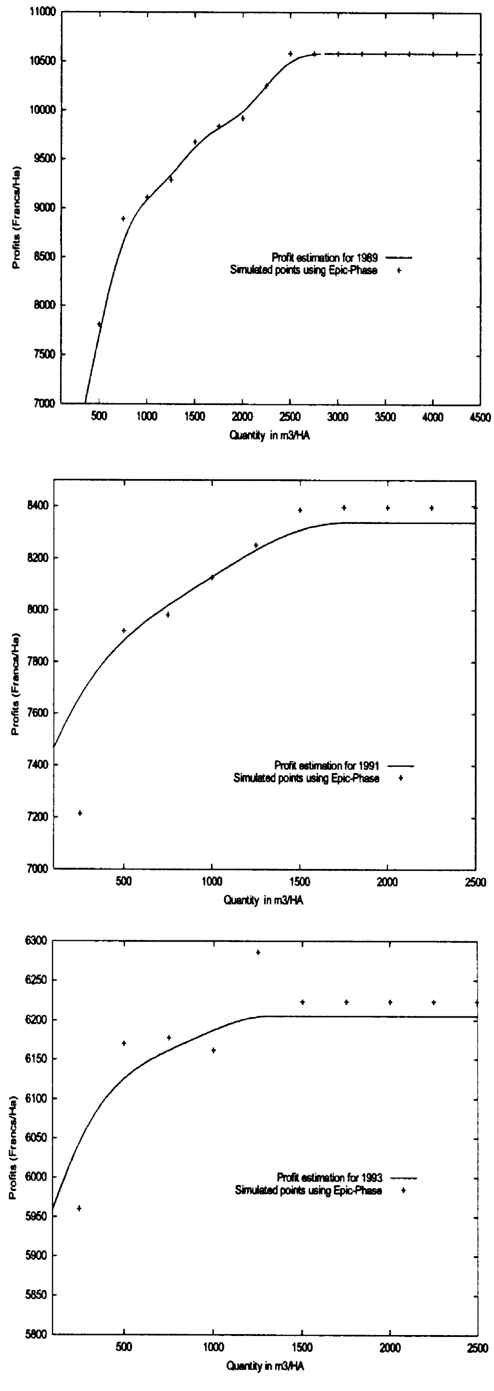

Figure 2. Profits functions for 'dry', 'medium' and 'wet' year.

Figure 2 shows the estimation of the maximized profit functions. These estimations are presented for each year considered in our study. Note that these estimated profit functions have the same trend; they increase to reach a peak that depends on weather conditions, and then remain constant at a maximum level.

This trend is due to the yield-water relation; from the agronomic knowledge we know that plant yield increases as water quantity increases below some maximum value, then the yield decreases while increasing water quantities (Hexem and Heady, 1978). The estimated profit functions have some similarity with yield-water functions except when water is no more a limiting factor; in this case, the profit remains constant. The maximum profits vary with weather conditions (they reach roughly 10500, 8400, and 6200 Francs per hectare for dry, medium and wet climates respectively), and are obtained for various quantities depending on the weather (these quantities are 2900, 1700, and 1350 m^3 per hectare for dry, medium, and wet weathers respectively).

The demand function estimations are directly derived from the estimated profit functions, as shown in Figure 3.

The results of the demand estimates in Figure 4 show clear differences in water demand for the three weather conditions. The drier the weather, the greater the irrigation water demand. However these curves present the same shape and trends. These three demand functions are decreasing and nonlinear.

Water prices being set at the range of 0.6 to 2.61 F/m^3, depending on weather conditions, induce a null water demand. From the water quantity available equal to 2900 m^3 per hectare in dry year, to 1700 m^3 per hectare in average year, and to 1350 m^3 per hectare, it is not in the farmer's interest to irrigate. The differences between these maximum quantities can be very important. Note that this water quantity increases twofold from the wet year to the dry one. These differences are due to precipitations.[9] Water demand will be all the more high so since precipitations will be low.

Another interesting feature is that the estimated water demand functions have inflexion points and can be decomposed into areas. At low water prices, irrigation water demand seems to be inelastic. On the other hand, demand appears more and more elastic as price increases. The price levels at which the changes in price-responsiveness appears depend on weather conditions and are ranging from 0.30 F/m^3 in wet year to 1.60 F/m^3 in dry year. Up to these prices the variations in water consumptions with respect to the change in prices appear quite significant. These results are confirmed by existing studies using programming methods in the literature on irrigation water demand (Montginoul and Rieu, 1996; Iglesias et al., 1998; Varela-Ortega et al., 1998).

The knowledge of the price thresolds provides crucial information for the policymaker in order to initiate a water pricing reform. The response to price signals in water saving strategies depends on climate conditions. For example, an increase of price in the range of 0 to 0.9 F/m^3 may not produce a significative reduction of

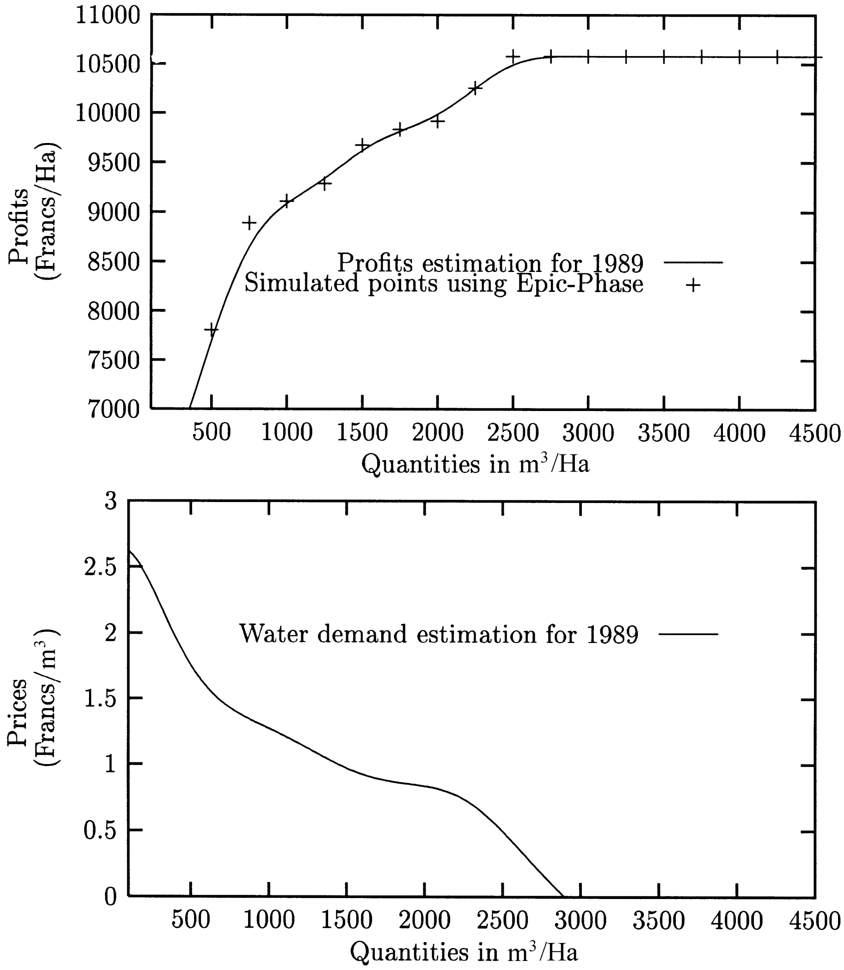

Figure 3. Profit and demand function for the 'dry' year (1989).

water consumption according to weather conditions; in a dry year, the consumption of water is not modified whereas under wet year, water demand becomes null. This aspect needs to be integrated in defining water pricing. If water savings are the policy objective, water prices need to be set at sufficiently high levels.

4. Conclusion

Our paper presents a methodology for evaluating irrigation water demand based on the evaluation of the farmer's willingness to pay for having one additional unit of water. Demand functions are obtained through a sequential making-decision

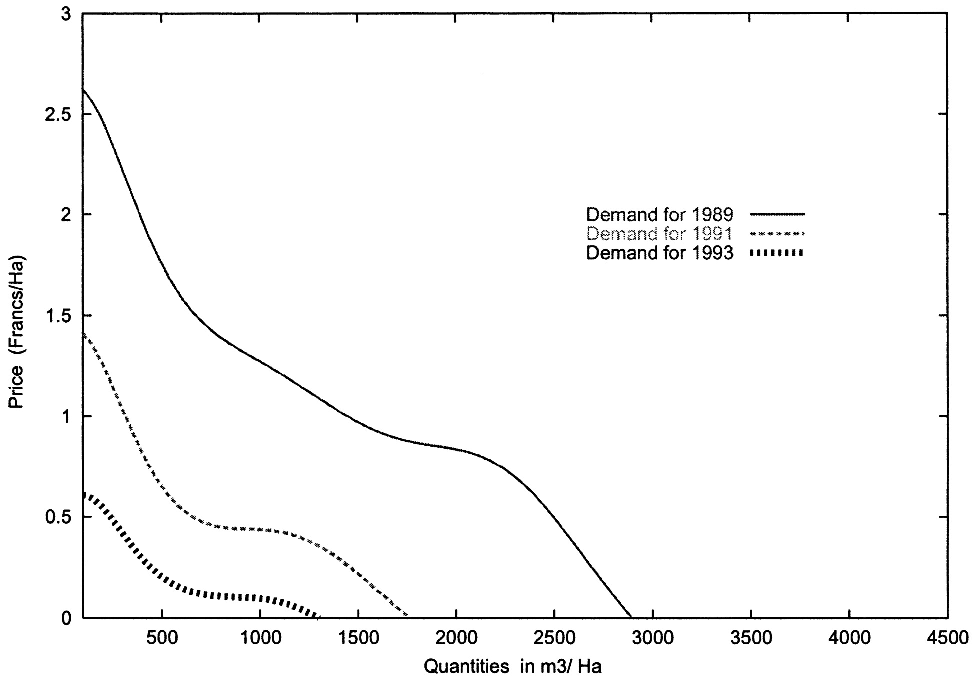

Figure 4. Demand functions for 'dry', 'medium' and 'wet' year.

program. The estimation procedure is based on data generated by a numerical method integrating a crop-growth model, an optimization procedure linked to a economic model, and nonparametric methods.

This method is applied to used to estimate demand functions for data prevailing in the South-West of France. We represent these functions for three representative climatic years. We show that irrigation water demands strongly depend on weather conditions, but have the same shape: they are decreasing and nonlinear. We can decompose each of them into two major areas: water demand is inelastic at low water prices and then becomes responsive to water prices up to some price level. The price levels at which water demand appears elastic depend on climates and vary around 0.30 F/m^3 for wet weather conditions up to roughy 1.60 F/m^3 for a dry year. Water policies have to include this information for defining pricing schemes taking into account climate.

Our method can also be used in a broader framework where the weather is unknown and the farmer decision process is stochastic. As time goes by, the farmer observes the climate and integrates this information in his decision process. The complexity of the resolution procedure is increased, but the method remains valid and operational. The demand function under stochastic condition can therefore be estimated (Bontemps and Couture, 2001) and the value of the information be quantified during the irrigation season (Couture, 2000a, 2000b).

Another natural extension concerns the problem of on-farm irrigation scheduling in order to take into account competition for water between crops. Using the proposed method, on-farm water demand function may be estimated in the same way. Due to the probable complexity of any on-farm model, some advanced numerical tools, such as genetic algorithm (Goldberg, 1989), may be needed.

Notes

[1] During summer, irrigated agriculture represents 80% of total water consumption in France.

[2] This problem has been mentioned by economists a long time ago, the first volume of the American Economic Review in 1911 contains a paper on this problem (Coman, 1911).

[3] This model is included as a yield-water response function in order to represent the production function. EPIC-PHASE is a crop growth simulator model.

[4] If the farmer does not irrigate, then $q_t = 0$.

[5] The set of constraints defined by (8) reduces the space of available irrigation schedules. Therefore the problem may be solved using an algorithm of search on all possible cases. Otherwise, we would have be obliged to use a global optimization program such as Genetic Algorithm (Goldberg, 1989), to find the optimal schedule.

[6] Estimations based on Epanechnikov kernel slightly differ from the Gaussian kernel estimator.

[7] Note that the Mack and Müller's estimator (1989) is easier to use for derivation since it has a denominator which does not depend on the derivative variable (Q here). Since the derivation calculus are quite obvious in our case, we have used the 'classic' kernel estimator, but we suggest to use this estimator for advanced derivation estimation.

[8] We have ran the simulation for only 19 value of quotas, mainly because the computation time for the agronomic model and the optimization procedure was important.

[9] The annual precipitations are 402.5 mm for 1989; 676.5 mm for 1991; 901.5 mm for 1993, in the considered area.

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