Energy crop supply in France: A min-max regret approach

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Paper prepared for presentation at the XIth International Congress of the EAAE (European Association of Agricultural Economists)
'The Future of Rural Europe in the Global Agri-Food System'
Copenhagen, Danemark, August 24-27, 2005

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Abstract

This paper attempts to estimate energy crop supply using an LP model comprising hundreds of representative farms of the arable cropping sector in France. In order to enhance the predictive ability of such a model and to provide an analytical tool useful to policy makers, interval linear programming (ILP) is used to formalise bounded rationality conditions. In the presence of uncertainty related to yields and prices it is assumed that the farmer minimises the distance from optimality once uncertainty resolves introducing an alternative criterion to the classic profit maximisation rationale. Model validation based on observed activity levels suggests that about 40% of the farms adopt the min-max regret criterion. Then energy crop supply curves, generated by the min-max regret model, are proved to be upward sloped alike classic LP supply curves.

Keywords : *Interval Linear Programming, Min-max Regret, Energy Crops, France*

JEL classification : C61, D81, Q18

Introduction

The main stumbling blocks in the development of biomass energy have been of a non-technical nature. Economics have undoubtedly been the principal obstacle, while the gaining of public acceptance is often equally important. Biofuel production gained momentum in France during 1993 when the revised European Common Agricultural Policy (CAP) imposed “set aside” land to cope with overproduction, decreased mechanical equipment use rate and damaged arable crop producers’ income. To minimise losses the European Commission allowed for non-food crop cultivation on land set aside. As a result, the French government decided to exempt biofuels from the Petroleum Products Excise to alleviate pressure on the income of numerous arable cropping farmers, while supporting agro-industry and refineries to exploit patents on biofuels and use idle capacity. An important part of the budget, which reached 150 million € in year 2000, is annually earmarked to finance biofuel excise tax exemption, allocated among the Ethyl Tertio Butyl Ether (ETBE) and Rapeseed Methyl Ester (RME) industry and the agricultural sector, namely wheat, sugar-beet and rapeseed producers. This policy has been criticised on efficiency grounds leading the government to revise the unitary tax exemption levels in 2002 at the expense of ethanol chain. Sourie et al. (2002) as well as Sourie and Rozakis (2001), have carried out studies of the French agricultural production of energy crops by means of mathematical programming. These studies reveal that agricultural raw material expenditure constitutes a significant part of the biofuel cost (table 1) so that a precise assessment of it would enhance the value of economic analyses on biofuels. This would enable welfare effects to be correctly estimated thus assisting in credible evaluation of public policy.

The above mentioned studies elaborated arable sector linear programming models, comprising hundreds of representative farms, that maximise farm income subject to the interdependencies of food and non-food crops. Different productive units, namely arable cropping farms act independently in a context of perfect competition. Such sector models are built upon a common sort of structure which arises in multi-plant models, known as a block angular structure (Williams, 1999). One common row is always the objective row whereas diagonally placed blocks of coefficients denote sub-models, each one corresponding to a representative farm. It is supposed that there are no other common rows (or common constraints), that is there is no question of allocation of scarce resources across farms. Therefore optimizing this model it simply amounts to optimizing each sub-problem with its appropriate portion of the objective that is equivalent to treating each farm as autonomous. This sector model can be updated to take into account policy changes and can be used to derive opportunity costs and supply curves of energy crops (Sourie, 2002).

Linear programming has proved to be one of the most powerful tools in the analysis of resource allocation choices at the firm and sector level. However, the introduction of alternative methods in order to consider risk at the level of the decision making (DM) unit when selecting among alternative activity levels seems necessary in the increasingly uncertain environment of European agriculture. The mass of detailed data at the farm level required by standard risk programming models makes it extremely difficult to collect for a sector model. Actual data at the regional level can though be used to determine variability of gross margins by crop in terms of intervals. For this reason, this paper proposes an interval programming approach when the DM (each farmer) has incomplete information on the objective function coefficients at the crop mix decision moment. It is assumed that beside the risk-neutral expected gross margin maximisation behaviour, risk-averse farmers may adopt the min-max regret criterion. Observed crop mix data for each representative DM unit reveal whether the farmer adopts risk averse or neutral behaviour. Therefore sub-models corresponding to risk-neutral farms are always specified as LP whereas those sub-models representing farmers that do not pretend perfect information on gross margins are specified as interval linear programming (ILP). In other words, the block angular sector model contains farms that maximise their gross margin but also farms that minimise the maximum regret. The sector model can be now identified to a hybrid model. Eventually rectified supply curves of energy crops are determined using the hybrid model.

In the following section uncertainty is introduced with a brief review of the literature devoted to interval programming as well as a formal definition of the Interval Linear Programming (ILP) problem is presented. In the third section the background sector LP model in block angular structure. Also the estimation of non-food crop opportunity costs per farm as well as methodology for deriving supply curves is presented. Results confirm that many firms (farmers) do not follow the profit maximisation rationale in cases of limited information on expected margins. Finally, supply curves determined from a combination of max profit and min-max regret utility functions, that is generated by the hybrid model will be outlined. Conclusions and discussion complete the paper.

Table 1. Opportunity costs of biofuels 2002

biofuel	quantity	Biofuel costs[§] in €/l			
	kt	Agriculture	Industry & transport	Co-products	Totals
ETBE wheat	132	0.08	0.27	-0.063	0.288
ETBE sugarbeet	920	0.076	0.2415	0	0.318
Rapeseed ME	880	0.3975	0.222	-0.1905	0.429

§ for supplied quantities of 317000 t ester, 152000t ETBE sugarbeet, 78000 t ETBE wheat
Ethanol to ETBE plant capacity 3000/hl/day
Ester plant capacity 120000 t per annum

Uncertainty and Interval Programming

In mathematical programming models, the coefficient values are often considered known and fixed in a deterministic way. However, in practical situations, these values are frequently unknown or difficult to establish precisely. Interval Programming (IP) has been proposed as a means of avoiding the resulting modelling difficulties, by proceeding only with simple information on the variation range of the coefficients. Since decisions based on models that ignore variability in objective function coefficients can have devastating consequences, models that can deliver plans that will perform well regardless of future outcomes are appealing. More precisely, an ILP model consists of using parameters whose values can vary within some interval, instead of parameters with fixed values, as is the case in conventional mathematical programming.

Many techniques have been proposed to solve the resulting problem. Shaocheng (1994) studied the case where all the model parameters are represented by intervals and the decision variables are non negative. Chinneck and Ramadan (2000) generalized their approach to the case where variables are without sign restriction. The case which is of greater interest for our purpose is the one where only the objective function coefficients are represented by intervals. This particular problem is the most frequently considered in ILP literature (Bitran, 1980, Steuer, 1981, Rommelfanger, 1989, Ishibushi and Tanaka, 1990, Inuiguchi and Sakawa, 1995, Mausser and Laguna, 1998, 1999a, 1999b). We now introduce some definitions and notations and briefly present the formal problem.

Interval Linear Programming (ILP) Problem

Let us consider a Linear Programming (LP) model with *n* (real and positive) variables and *m* constraints. The objective function is to be maximized. Formally:

$$\max = \{cx : c \in \Gamma, x \in S\} \qquad \text{(ILP)}$$

where

$$\Gamma = \{c \in \Re^n : c_i \in [l_i, u_i], \forall i = 1..n\}$$

$$S = \{x \in \Re^n : Ax \leq b, x \geq 0, A \in \Re^{m \times n}, b \in \Re^m\}$$

Let $\Pi = \{x \in S : x = \arg\max\{cy : y \in S, c \in \Gamma\}\}$ be the set of potentially optimal solutions. Let Y be the set of all the extreme objective functions: $\mathrm{Y} = \{c \in \Gamma : c_i \in \{l_i, u_i\}, \forall i = 1..n\}$.To give insight into what the problem becomes when intervals are introduced, we recall the following theorem (Inuiguchi and Sakawa, 1995, Mausser and Laguna, 1999b):

Theorem 1

Let us consider the following multiobjective linear programming problem:

$\upsilon\text{-}max\{\mathbf{cx} : \mathbf{x} \in S; c \in Y\}$ *(MOLP)*

where the υ-max notation stands for the vector maximization. Then, a solution is a potentially optimal solution to (ILP) problem if, and only if, it is weakly efficient to the (MOLP) problem.

Theoretically, this result enables us to mobilize all the tools and concepts of multi-objective linear programming literature, especially to choose/propose suitable solution concepts for (ILP) problem. In the literature, two distinct attitudes can be observed. The first attitude consists of finding all potentially optimal solutions that the model can return in order to examine the possible evolutions of the system that the model is representing. The methods proposed by Steuer[18] and Bitran[11] follow this kind of logic. The second attitude consists of adopting a specific criterion (such as the Hurwicz's criterion, the maxmin gain of Falk, the minmax regret of Savage, etc.) to select a solution among the potentially optimal solutions. Rommelfanger (1989), Ishibuchi and Tanaka (1990), Inuiguchi and Sakawa (1995) and Mausser and Laguna (1998, 1999a, 1999b) proposed different methods with this second perspective. Following this perspective, the next section introduces the approach that we have selected, namely the minimization of the maximum regret approach, and the procedure we adopted for its implementation.

Minimizing the Maximum Regret

Minimizing the maximum regret consists of finding a solution which will give the decision maker a satisfaction level as close as possible to the optimal situation (which can only be known as a *posteriori*), whatever situation occurs in the future. The farmers are faced with a highly unstable economic situation and know that their decisions will result in uncertain gains. It seems reasonable to suppose that they will decide on their surface allocations *prudently* in order to go through this time of economic instability with minimum loss, while trying to obtain a satisfying profit level. This is precisely the logic underlying the minmax regret criterion; i.e. selection of a *robust* solution that will give a high satisfaction level whatever happens in the future and that will not cause regret (Loomes and Sugden, 1982). Therefore, we make the hypothesis that the farmers of the considered region adopt the min-max regret criterion to make their surface allocation decisions. The mathematical translation of this hypothesis for the arable sector supply model was to implement the minmax regret solution procedure proposed in the literature (Inuiguchi and Sakawa, 1995, Mausser and Laguna, 1998, 1999a, 1999b). The presentation of the formal problem and the algorithm of minmax regret are presented in the next paragraphs.

The MinMax Regret (MMR) Problem

Suppose that a solution $x \in S$ is selected for a given $c \in \Gamma$. The regret is then:

$$R(c, x) = \max_{y \in S}\{cy\} - cx$$

The maximum regret is:

$\max_{c\in\Gamma}\{R(c,x)\}$

The *minmax* regret solution $\hat{x}$ is then such that $R_{\max}(\hat{x}) \le R_{\max}(x)$ for all $x \in S$. The corresponding problem to be solved is:

$$\min_{x\in S}\{\max_{c\in\Gamma}\{\max_{y\in S}\{cy\} - cx\}\} \qquad \textit{(MMR)}$$

The MinMax Regret Algorithm

The main difficulty in solving (*MMR*) lies into the infinity of objective functions to be considered. Shimizu and Aiyoshi (1980) proposed a relaxation procedure to handle this problem. Instead of considering all possible objective functions, they consider only a limited number among them and solve a relaxed problem (hereafter called (*MMR'*)) to obtain a candidate regret solution. A second problem (called hereafter (*CMR*)) is then solved to test the global optimality of the generated solution. If the solution is globally optimal, the algorithm terminates. Otherwise, (*CMR*) generates a constraint which is then integrated into the constraint system of (*MMR'*) to solve it again for a new candidate solution. This process continues in this manner until a globally optimal solution is obtained. The relaxed (*MMR'*) problem is:

$$\min_{x\in S}\{\max_{c\in C}\{\max_{y\in S}\{cy\} - cx\}\} \qquad (\textit{MMR'})$$

where $C = \{c^1, c^2, ..., c^p\} \subset \Gamma$. This problem is equivalent to:

$\min r$ (*MMR'*)

s.t. $r + c^k x \ge c^k x_{c^k}$, $k = 1, \dots , p$

$r \ge 0,\ x \in S,\ c^k \in C$

where x_{c^k} is the optimal solution of $\max_{y\in S}(c^k y)$. A constraint of type $r + c^k x \ge c^k x_{c^k}$ is called a regret cut. Let us denote $\bar{x}$ the optimal solution of (*MMR'*) and $\bar{r}$ the corresponding regret. Since all possible objective functions are not considered in (*MMR'*) we cannot be sure that there is no *c* belonging to $\Gamma \setminus C$ which can cause a greater regret by its realization in the future. Hence, we use the following (CMR) problem to test the global optimality of $\bar{x}$:

$$\max_{c\in\Gamma}\{\max_{y\in S}\{cy\} - c\bar{x}\} \qquad \textit{(CMR)}$$

Observe that the objective function value of (CMR) represents the maximum regret for $\bar{x}$ over Γ, denoted by $R_{\max}(\bar{x})$. If the optimal solution $x_{c^{p+1}} \in S, c^{p+1} \in \Gamma$ of (CMR) gives $R_{\max}(\bar{x}) > \bar{r}$, it means that c^{p+1} can cause a greater regret than $\bar{r}$ by its realization in the future and that it has to be considered also in C while solving (*MMR'*). So, the regret cut $r + c^{p+1}x \ge c^{p+1}x_{c^{p+1}}$ is added to the previous constraint set of the (*MMR')* to solve it again and obtain a new candidate. The process is iterated until the generated candidate regret solution is found to be optimal by (CMR). This solution procedure idea is summarized by the following algorithm:

Step 0: $r^\circ \leftarrow 0, k \leftarrow 0,$ choose an initial candidate $\bar{x}$

Step 1: $k \leftarrow k+1,$ Solve (CMR) to find c^k and $R_{\max}(\bar{x})$:

If $R_{\max}(\bar{x}) = r^\circ$ then END. $\bar{x}$ minimize the maximum regret.

Step 2: Add the regret cut $r + c^k x \geq c^k x_{c^k}$ to the constraint set of (*MMR'*)

Step 3: Solve (*MMR'*) to obtain a new candidate $\bar{x}$ and $\bar{r}$. $r^\circ \leftarrow \bar{r}$. Go to Step 1.

The difficulty in this resolution process lies in the quadratic nature of the (CMR) problem. Inuiguchi and Sakawa (1995) investigated the properties of the minmax regret solution to find a more suitable way to solve (CRM). Mausser and Laguna (1998) used their results to formulate a mixed integer linear program equivalent to (CMR) to obtain the regret-maximizing costs which is less costly to solve. As Mausser and Laguna (1999a) noticed that the complexity of that mixed integer program severely limits the size of problems to be addressed, therefore they suggested to use heuristics. In this case though, uncertain objective function coefficients are in no farm decision making unit more than 10. Thus, in our experiments we used this equivalent problem mixed-integer formulation.

Mathematical modelling and opportunity costs of non-food arable crops

The raw material costs, defined at the farm level, form a significant part of the bio-fuel cost. In the French context, this share varies between 20 and 25 % for wheat or sugar-beet and 60 to 65 % for rapeseed (Sourie & Rozakis, 2001). Due to an important spatial dispersion of bio-fuel raw material in many productive units (farms) and competition between agricultural activities for the use of production factors (land in particular), strongly dependent on the CAP, the cost estimates of these raw materials raise specific problems. Thanks to supply models, based on linear programming, it is possible to correctly estimate these costs, their diversity and finally to aggregate them in order to obtain raw material supply for industry. Although it is important that this cost be estimated correctly, three principal difficulties are faced: -

Firstly, the scattering of the resource. Currently, France has more than 50 000 energy crop (wheat, beet, and rapeseed) producers according to the professional association of oil-seed growers (ONIOL, 2002). Since different farms have neither the same productivity nor the same economic efficiency, the production costs will be variable in space. In this context, average cost is not a suitable concept.

Secondly, the competition existing between agricultural activities and non-food crops at the farm level. In order to satisfy agronomic constraints when introducing non-food crops, food rotation may be altered. This competition imposes a minimum level of profitability for non-food crops. We cannot consider the food activities and the non-food activities as independent so this implies that the full cost valuation method results, which do not take into account endogenous dependences between crops, may be a misleading indicator to predict farmers' decisions regarding energy crop cultivation.

Finally, the dependence of raw material costs on agricultural policy measures. The changes in agricultural policy, for example, a modification of the obligatory set-aside land rate or of the levels of direct subsidies to crops, affect the opportunity costs. Thus, the set-aside land obligation that has been included in the revised CAP measures implemented since 1993, and the authorization to cultivate only non-food crops on land obligatorily set aside, contributed to a decrease in the biofuel raw material cost. If the set-aside obligation disappears, an increase in the costs of crops grown on land set-aside, specifically non-food crops, will immediately follow.

The microeconomic concepts of supply curve and opportunity cost make possible a solution to these difficulties. These concepts could be elaborated in a satisfactory way by using mathematical programming models, called supply models, based on a representation of farming systems. This approach also leads to an estimate of the agricultural producers' surplus, which is an item of the cost-benefit balance of bio fuels.

It is postulated that the farmers choose among food crops X_c and non-food crops X_d so as to maximize the agricultural income of their farm. Thus, each producer f maximizes an objective function represented by expression (1). Variables X_u take their values in a limited feasible area defined by a system of institutional, technical and agronomic constraints (relationships 2-11).

Arable agriculture supply model specification is defined below :

Indices

$u \in U$	crop index, (c=1 for wheat, 2: wheat monoculture, 3: wheat after peas, 4: wheat in set aside, 5: barley, 6: winter barley, 7: corn, 8: fresh peas, 9: rape-seed, 10: sunflower, 11: peas, 12: potatoes, 13: sugar beets, 14: green beans, 15: sugar beet-ethanol, 16: wheat-ethanol, 17: rapeseed-ester, 18: land set aside)
$c \in C \subset U$	index for the subset of food crops, $C=\{1, \ldots, 14\}$
$d \in D \subset U$	index for the subset of energy crops, $D=\{15, 16, 17\}$ ($\lvert D \rvert = m$)
$i \in I \subset U$	index for the subset of food crops upon which set aside is calculated, $I=\{1, \ldots, 11\}$
$h \in H \subset U$	index for crops demand quota, H= $\{8, 12, 13, 14\}$
$t \in T \subset U$	index for crops preceding wheat, $T=\{7, 8, 9, 10, 12, 13, 14, 15, 17, 18\}$
$g_1 \in G_1$	index for crops that belong to group 1, $G_1= (\{1\text{-}6\}, \{9, 10\}, \{13, 15\}, \{9\}, \{10\})$
$g_2 \in G_2 \subset U$	index for crops that belong to group 2, $G_2= (\{8\}, \{11\}, \{5\})$
$f \in F$	index for farms
$k \in K$	index for agronomic constraints

Parameters

$gm_{c,f}$	gross margin for food crop c grown on farm f (€/ha)
p_d	price at the farm gate for energy crop d (€/t)
$y_{d,f}$	yield of energy crop d grown on farm f (t/ha)
s_d	subsidy paid to farmers for energy crop d (€/ha)
$c_{d,f}$	production cost for energy crop d on farm f (€/ha)
γ	subsidy to land set aside (€/ha)
w_f	multiplier used to scale up arable land of farm f to the national level
σ_f	total arable land available on farm f (ha)
$\sigma_{1,f}$	land available on farm f for sugar-beet for sugar production (ha)
θ	fraction of arable land that must be set aside (for 1998: 10 % of total land with cereal, oil and protein seeds)
$\overline{x}_{h,f}$	maximum
π_k	maximum fraction of land permitted for crops included in agronomic constraint k

Decision Variables

$x_{c,f}$	area allocated to food crop c on farm f (ha)
$x_{d,f}$	area allocated to energy crop d on farm f (ha)

$$\max \sum_{f \in F} \sum_{c \in C} gm_{c,f} x_{c,f} + \sum_{f \in F} \sum_{d \in D} \left(p_d y_{d,f} + s_d - c_{d,f} \right) x_{d,f} + \gamma x_{18,f} \qquad (1)$$

subject to:

Land resource constraints $\sum_{u \in U} x_{u,f} \leq w_f \sigma_f$ $\forall f \in F$ (2)

Set aside constraints: $\sum_{d \in D} x_{d,f} + x_{18,f} \geq \theta_{\min} w_f \left(\sigma_f - x_{i,f}\right)$ $\forall f \in F$ (3)

$\sum_{d \in D} x_{d,f} + x_{18,f} \leq \theta_{\max} w_f \sigma_f$ $\forall f \in F$ (4)

Quotas on demand $x_{h,f} \leq \bar{x}_{h,f}$ $\forall h \in H, \ \forall f \in F$ (5)

wheat set-aside $x_{4,f} \leq x_{15,f}$ $\forall f \in F$ (6)

Rotation wheat $x_{1,f} \leq \sum_{t \in T} x_{t,f}$ $\forall f \in F$ (7)

Rotation wheat-peas $x_{3,f} \leq x_{11,f}$ $\forall f \in F$ (8)

Agronomic limits 1 $\sum_{u \in G_1} x_{u,f} \leq \pi_{g_1} w_f \sigma_f$ $\forall g1 \in G1, f \in F$ (9)

Agronomic limits 2 $x_{g_2,f} \leq \pi_{g_2} w_f \sigma_f$ $\forall g2 \in G2, f \in F$ (10)

Non-negativity constraints: $x_{u,f} \geq 0$ $\forall u \in U, f \in F$ (11)

The fallow land obligation is explicitly formalized because of the very significant role it plays on the cost of non-food resources. Let $I \subset U$ be the food crops that do not involve set aside obligation (for example, sugar-beet) then the fallow constraint at the rate of 10% is shown in (3) and (4). In other words, the area of the non-food crops and land set-aside must at least be equal to 10% of the extent of the farm, minus the coverage of the crops not subject to the set-aside obligation. This constraint, which is the main determinant factor of the opportunity cost, implies competition between the non-food crops and fallow land, and at the same time saves energy crops against more competitive food crops.

Within the framework of a price negotiation regarding the raw materials, it is traditional to calculate the cost value even if, in agriculture, this concept presents well known problems. This is firstly, because of the existence of non commercial factors such as agricultural family labour, agronomic value of heads of rotations, and secondly due to estimates of certain factors without relationship to their economic value; for example, the land factor. To carry out a public assessment of bio-fuel policy, which is the main purpose of this exercise, it will be more appropriate to refer to the opportunity cost (marginal) instead of the (average) cost value because of its rigorous determination and precise economic meaning. More precisely, the opportunity cost will give the minimal price which allows the introduction to the arable cropping system of a given quantity of non-food crop into a rotation, without reducing the farm agricultural income.

The opportunity cost is obtained in the following way:

Firstly, transforming the coefficients of the non-food cultures in the objective function (1), by removing the sales component, (thus there remain variable expenses + subsidies/ha) :

$$\max \sum_{f \in F} \sum_{c \in C} g_{c,f} x_{c,f} + \sum_{f \in F} \sum_{d \in D} \left(s_d - c_{d,f}\right) x_{d,f} + \gamma x_{18,f} \qquad (12)$$

At the optimum of (12) under constraints (2)-(11), surfaces cultivated by energy crops will be zero, the fallow land occupying all the surface imposed by constraints (3) and (4).

Consider a production of a minimal quantity ***q*** of a crop x_d by setting down the constraint $y_d\, x_d$ **>*q*,** where y_d represents the yield of the energy crop ***d*.** The objective function will decrease and the model will automatically calculate a result which is interpreted as the cost of the last unit produced to reach **q.** It is the opportunity cost estimate. This result is an output of any optimization model under constraints, known as its shadow price equal to the constraint dual value. The opportunity cost will vary according to the produced quantities **q,** within each farm but also across farms when the constraint applies to all farms ($\overline{Q}_d$ non-negative quantities of non-food resources):

$$\sum_{f \in F} y_{d,f} x_{d,f} \geq \overline{Q}_d \qquad \forall d \in D \qquad (13)$$

Thus, the energy crop supply takes into account competition with other non-food as well as food crops in a large number of farms. These results underline the interdependence between arable crops as well as cross-price dependencies.

The national model is a set of individual farm models, suitably weighted to obtain a representative image of the farms able to produce non-food cultures. Let F be the set of farms and **W** the respective weights. The objective function of the national model is now relationship (12) and the feasible area is defined by the constraints (2) to (11) and (13) that corresponds to *d* supply constraints, as common constraints to the *f* individual farm models. The dual values of the binding constraints **(**13**)** give the minimal prices p_d^* that the industry must pay the producers in order to obtain the demanded quantity $\overline{Q}_d$. Non-food crop production is distributed in an optimal way among the various farms ***f*,** so that reduction in the objective function value, i.e. the total cost of production, becomes minimum. By increasing the quantity $\overline{Q}_d$**,** one obtains the corresponding p_d^***.** The relation $p_d^* = J_d(q_d)$ is a (inverse) supply curve of the resource ***d*.**

If the optimal distribution of production is not satisfactory when taking into consideration the equity criterion or other political criteria, the model could be modified by imposing rules of sharing out non-food crop production among farms. Consequently, the opportunity cost will be higher, as the solution of the modified model shows. Different values of the parameters in the model (for example, the rate of obligatory set-aside or of the quantity of bio-fuel to be produced) gives rise to a new supply curve. Thus, for each non-food crop *d***,** there exists a family of supply curves.

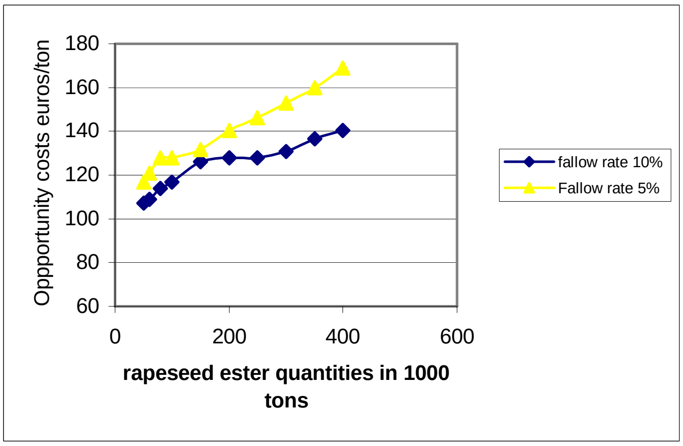

Figure 1. Rapeseed supply curves, in €/t

For example, when the quantity of ester is parameterised between zero and 500 000 tons, for two set-aside land rates, two supply curves are obtained as shown in figure 1. A decrease in these rates involves an increase in the opportunity cost because additional producers that are less efficient enter the market to satisfy the bio-fuel demand.

Case study and model validation

The model implemented here comprises in total 681 farms from the two main arable cropping regions of France (with 216 and 465 farms located in the cereal and sugar-beet region respectively). Farm Accounting Data Network (FADN) data on number of farms per type, surfaces cultivated, and land set aside concerning the above farm types have been used in this exercise, along with detailed data on inputs of arable crops used by each farm. These farms adequately represent the diversity of arable cropping system in Central and Northern France where energy crops are mostly cultivated. Relevant weights have been used to project cultivated surfaces in the sample to the national levels observed in the base year 2000. Profiles of the crop mix are shown in Table 2 by region. Each individual farm model has up to 18 variables corresponding to arable crops historically cultivated in the farm.

Table 2. Crop mix by region aggregates

	sugarbeet region				cereal region			
	Observed surfaces in ha	Observed crop mix	LP optimal crop mix	Relative percentage to total surface	Observed surfaces in ha	Observed crop mix	LP optimal crop mix	Relative percentage to total surface
Wheat	1915401	47.4%	51.9%	4.48%	2813264	36.1%	40.5%	4.54%
Barley	184431	4.6%	3.1%	1.49%	661293	8.5%	7.1%	1.31%
Spring barley	328213	8.1%	5.9%	2.24%	1052023	13.5%	19.4%	5.96%
Maize	0	0.0%	0.0%	0.00%	436967	5.6%	2.7%	2.91%
Fresh peas	43103	1.1%	1.1%	0.00%	0	0.0%	0.0%	
Rape seed	61167	1.5%	3.8%	2.26%	1875315	24.0%	22.5%	1.50%
Sunflower	0	0.0%	0.0%	0.00%	117546	1.5%	0.9%	0.65%
Peas	452174	11.2%	9.8%	1.38%	0	0.0%	0.0%	
Potatoes	157142	3.9%	3.9%	0.02%	0	0.0%	0.0%	
Sugarbeet	603479	14.9%	14.5%	0.41%	0	0.0%	0.0%	
Beans	13257	0.3%	0.3%	0.00%	0	0.0%	0.0%	
Sgbeet EtOH	0	0.0%	0.0%	0.00%	0	0.0%	0.0%	
Wheat EtOH	15234	0.4%	5.3%	4.97%	0	0.0%	0.0%	
Rapeseed ME	102382	2.5%	0.4%	2.14%	310229	4.0%	1.2%	2.75%
Set aside	162726	4.0%	0.0%	4.02%	536704	6.9%	5.7%	1.21%
	4 038 709	100.0%	100.0%	23.42%	7 803 341	100.0%	100.0%	20.84%

The validity of the arable sector model has been evaluated by comparing optimal activity level outcome of the model with the actual ones. To evaluate the proximity of LP model solution x_k^{opt} to the observed activity level x_k^{obs} for the crop *k*, we used the following distance measure:

$$M_1^{opt}\left(x^{opt}\right) = \frac{L_1\left(x^{opt}, x^{obs}\right)}{TotalLand} = \frac{\sum_i \left|x_i^{opt} - x_i^{obs}\right|}{\sum_i x_i^{obs}} \qquad (14)$$

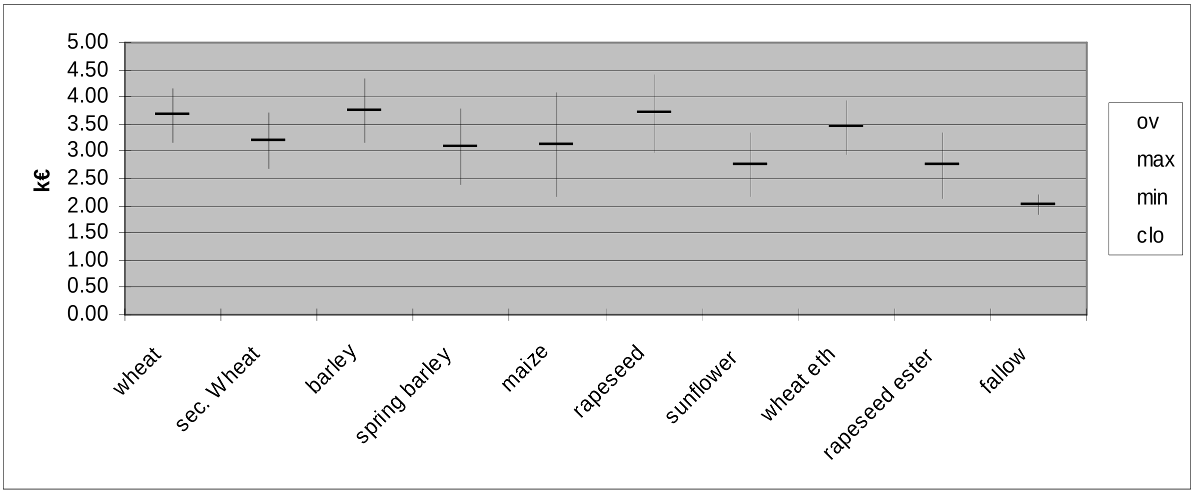

Figure 2. gross margin variability intervals

As shown in Table 2 concerning the cereal oriented region, rape-seed for food and energy as well as sunflower cultivated surfaces are underestimated whereas cereals are overestimated. The difference in absolute value between the observed production levels and the optimized allocations (in other words, the distance between the two solutions using a L_1 metric) is approximately 1.8 million ha. The total arable land considered being 7.8 million ha, the relative distance (the difference between the two solutions in absolute value divided by the total arable land) is about 20%. In the sugar-beet specializing region the relative aggregate distance is about 23%. The fit is usually better at the aggregate level than at the farm level as compensatory effects counteract making the model results to approach the observed crop mix. As a matter of fact at the elementary farm level, distances become more important: the relative average distance is about 37% with standard deviation of 22% (in the sugar-beet region 45% average with 16% standard deviation).

Hence, the need for further calibration of the model is clear. In all evidence, such variations can occur for two reasons: an inaccurate specification of the feasible region of the model or an inaccurate specification of the objective functions. In this exercise, we assume that the feasible region of each elementary model adequately represents the allocation possibilities of the farmers. Let us note that the observed solutions for each farm have been verified to be feasible in the corresponding model. Regarding the objective function specification, it is reasonable to suppose that in a relatively stable environment farmers will base their decisions on average prices. The LP supply model is originally designed under this very assumption: objective function coefficients (the gross margins per crop) are calculated based on the 1993-1997 price and yield averages. However, in the present context, with subsequent CAP reforms that downgrade subsidy stability factor in the formation of gross margin, the natural uncertainty about yields combined with an increasing uncertainty about prices enlarge the gross margin variation range. Figure 2 illustrates variability of gross margins for crops observed in the sample due to yield and price variations. Total uncertainty can be represented by the range determined by $\mu \pm 2\sigma$, where μ is the mean value and σ the standard deviation of the gross margin distribution, calculated in the year 2002 conditions. Thus, we opted for investigating the problems that may arise because of a possibly inaccurate specification of the objective functions. In other words, an implicit assumption is that the objective function coefficients, which correspond to unit gross margins per crop, are perceived by farmers as imprecise numbers rather than crisp values. Therefore they will be represented in the model by intervals transforming the original LP to an interval linear programming problem.

The interval linear programming approach with the minmax regret criterion objective function has been implemented to investigate if the model validity can be improved by this approach. The GAMS software (Brooke et al., 1998) is used to implement the proposed minmax regret algorithm using the linear and integer programming modules of the CPLEX solver[1]. Gross margin intervals have been used in the model for crops that appear in the graph in Fig.2, so that, the number *s* of interval-valued coefficients can be up to 9. For the initial regret candidates to start the algorithm, we used the LP optimal solutions.

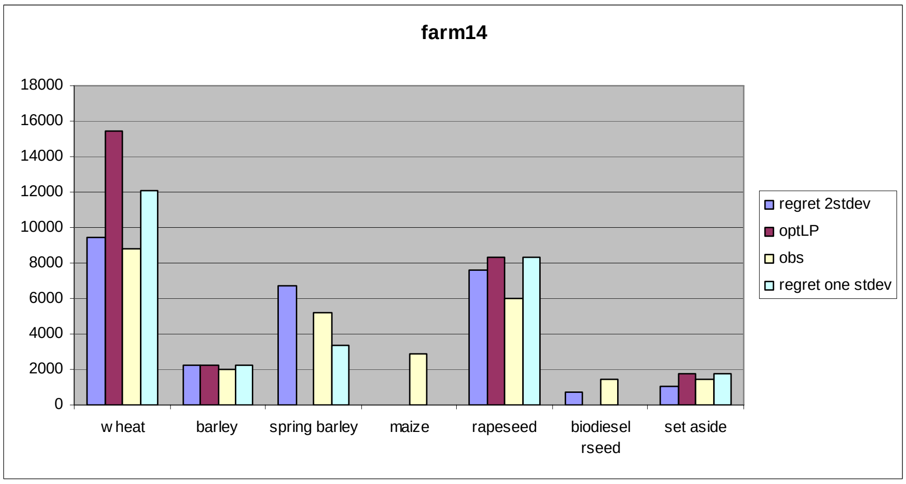

Figure 3. Comparison of the min-max regret solutions (gross margin variation for all crops equal to one and two standard deviations) with the actual (observed) and the Optimal LP Solutions at the farm level (surfaces in ha).

The principal effect of the ILP approach with the MinMax Regret is: when the difference between the gross margins is relatively small, the minmax regret approach gives more "balanced" solutions, more so when the interval coefficients get larger. In fact, as the intervals get larger, the gross margins for different crops start to overlap or, if they already have an intersection, this increases. It then becomes more difficult for the farmer to anticipate which crop will be more profitable. Hence, the min-max regret approach tends to return more and more balanced solutions as the size of the intervals increase. Figure 3 illustrates that point, in a cereal farm (with $M_1^{opt} = 34\%$) where, at the LP optimal solution, wheat is selected at the expense of spring barley and energy rapeseed. A detailed discussion on this point is presented by Kazakci and Vanderpooten (2002). The effects of the min-max regret approach on the proximities to the observed crop mix obtained at the microscopic level are considerable: for about 38% of the farms, the relative distance ($M_1\left(x^{\min\max}\right)$) of the minmax regret solution to the corresponding observed solution is smaller than the relative distance (as defined in equation 14) of the LP's optimum solution to the observed one. The opposite is true for 18% of the farms while both objective function specifications give identical solutions for the rest of the farms. Concerning the improvement in the proximities to the observed solutions, the worst proximities ($\max\left(M_1^j\right)$) obtained for these 38% of the farms provide an average improvement of 10% with respect to the LP's proximities.

Thus some farmers maximize gross margin while others demonstrate risk averse attitude in the sense of minimising the maximum regret. For each individual farm elementary model a simple algorithm replaces the objective function with that, between gross margin maximization and min-max regret, performing better in terms of proximity of the resulted crop mix to the observed one. This way we end up with a *hybrid* regional model with custom objective function for each representative farm. This model has by definition a higher predictive capacity than the initial LP, so it will be used to generate energy crops' supply curves. For this purpose the procedure proposed in section 1 is applied adapted to host minmax regret terms in the aggregate objective function. Then a constraint common to all farms obliges the model to produce fixed quantities of energy crops.

[1] the model is available from the authors upon request

Different factors affect the relative position against classic LP generated supply curves. Not only because the objective function value in terms of total farm gross margin at the minmax regret optimum is lower than the LP optimal value (results in lower opportunity cost), but also that the energy crop giving relatively stable gross margin is appreciated in the farm comparing with other crops with high variability (higher opportunity cost). Depending on the above factors, as well as the interaction with the constraint structure, the minmax supply curves are located to the right of the LP curve up to a certain quantity level. Quantities used in the biofuel industry float in this range, thus we consider that the min-max criterion adoption results in lower opportunity costs of biomass raw material for the biofuel industry. For actual levels of biofuel production, quantities and costs of biomass are shown in Table 3. The difference between biofuel estimated cost and its market value indicates the minimal subsidy (equivalent to the excise tax exemption) necessary to make biofuels financially viable. Biofuel costs calculated using minmax regret objective functions are 5% lower than their LP counterparts.

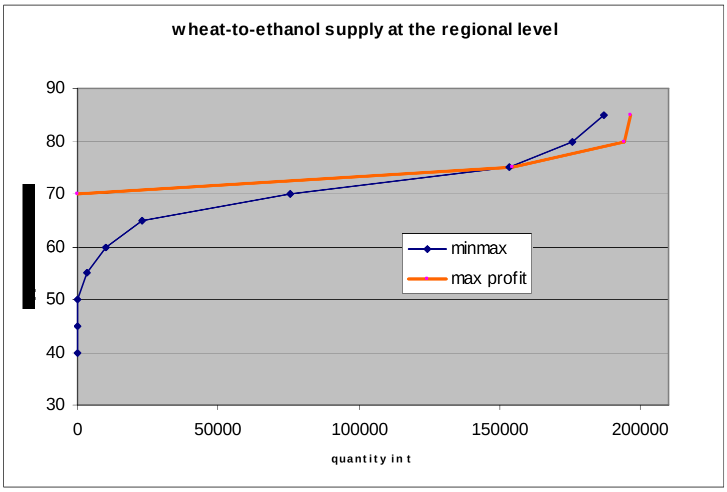

Figure 4. Supply curves resulted by max profit and min-max regret objectives at the regional level

Conclusions and discussion

This analysis underlines different factors that determine the agricultural raw material cost used for the production of bio-fuels. Certain factors are endogenous to the farms such as crop yields; other factors are exogenous such as agricultural policy decisions, in particular those that relate to the rate of land set-aside. Climatic risks are also a source of cost variation. In addition to cost variation factors that are farm specific, spatial variability exists, which is the result of differences in economic efficiency among farms. The concepts of agricultural supply and opportunity cost resulting from the microeconomic theory, which find an application within the framework of mathematical programming models, allow for modelling of the agricultural complexity with very interesting results. Energy crop supply curves are thus generated so that a biofuel system partial equilibrium model assists to understand cost levels for different agents, as well as surpluses allocation.

In order to enhance the predictive ability of such a model to provide an analytical tool useful to policy makers, interval linear programming (ILP) is used to formalise bounded rationality conditions caused by uncertainty related to yields and prices. Recent advances in operational research are exploited, permitting to minimise the distance from optimality once uncertainty resolves introducing an alternative criterion to the classic profit maximisation rationale. Model validation based on observed activity levels suggests that about 38% of the farms adopt the min-max regret criterion. Farmers' decisions are not exclusively explained by the expected profit maximization logic underlying LP models. Moreover, in the cases where the farmers choose a balanced crop mix, the min-max regret solutions tend to improve the representative capacity of the model.

Energy crop supply and opportunity costs determined by the hybrid maximum profit and min-max regret aggregate model, are proved to be upward sloped and slightly displaced to the right (less costly energy crops) compared with classic LP supply curves. Opportunity costs aggregation to supply curves of energy crops results in aggregate supply curves consistent to the theory when a sufficiently large number of elementary producers are involved. To paraphrase Simon[2]: "..empirical data do confirm that supply curves generally have positive slopes.. but positively sloped supply curves could result from a wide range of behaviours satisfying the assumptions of bounded rationality rather than those of utility maximisation".

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