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# Comparative Performance of Selected Mathematical Programming Models

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Paper prepared for presentation at the X<sup>th</sup> EAAE Congress 'Exploring Diversity in the European Agri-Food System', Zaragoza (Spain), 28-31 August 2002

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# Abstract

This study compares the predictive performance of several mathematical programming models. Using the cropping patterns, yields and crop gross margins of eighteen farms over a period of five years we compare the models' optimum solutions with observed crop distributions after the Reform of the EU Common Agricultural Policy of 1992. The results show that the best prediction corresponds to a model that includes expected profit and a qualitative measure of crop riskiness. The results suggest that, in order to obtain reliable predictions, the modelling of farmers' responses to policy changes must consider the risk associated with any given cropping pattern. Finally, we test the ability of the proposed model to reproduce the farmers' observed behaviour with equally good performance under conditions of limited data availability.

Keywords: model performance, mathematical programming, modelling, decision-making.

# 1. Introduction

# The use of models for agricultural policy analysis

Agricultural policy analysis is often based on mathematical programming models. A desirable feature of the programming exercise is the ability to capture both the agricultural characteristics of the system and the farmer's decision-making process. However, due to the lack of data on the specific system to be modelled, average aggregated data are frequently used instead. This loss of information makes predictions of farmers' responses to policy changes imprecise at best.

Any changes in cropping pattern that occur in the wake of a policy reform have decisive effects on the economic, social and environmental aspects of the agricultural system. The accuracy of predictions is vital to the correct assessment of the impact of such policy changes. In this sense, there is a trade-off between the accuracy of predictions and the amount of data

required to build the model. The present study is an attempt to find a reasonable equilibrium between simplicity and accuracy.

The paper therefore assesses the ability of a number of mathematical programming models to predict farmers' decisions regarding crop distribution We measure the accuracy of each model by comparison of its optimum values with observed crop distributions. The range of models includes both single-criteria models (maximization of expected profit, safety-first model and positive mathematical programming) and multicriteria approaches (additive utility function and goal programming). To these we add a basic model based on previous average crop distribution with no area payments.

#### Literature review

In comparison with the econometric approach to agricultural policy analysis, it is rare to find works that test the forecasting capabilities of mathematical programming models. Of the few is worth mentioning Barnett *et al.* (1982), whose paper analyses the performance of goal programming *versus* expected profit maximization. They did not find differences in performance between goal programming and expected profit maximization. Herath *et al.* (1982) consider single (profit)-attribute utility maximization, two-attribute utility maximization and expected profit maximization. Their results showed that single-attribute utility maximization outperformed the bi-attribute utility model. The worst performance was offered by the expected profit maximization model.

Mohd (1984) also compared the expected profit model with the negative exponential utility and the market-based profit models to explain farmers' decisions regarding crop selection. In his paper, the expected profit maximization model performed better than the negative exponential utility and the market-based profit models in predicting observed crop distributions. Atwood *et al.* (1986) tested the consistency of risk programming models (profit maximization, Target-MOTAD, and MOTAD) over a 10-year period. According to them, further research is needed to explore the influence of the farms' financial situation on the model predictions. Weersink and Tauer (1989) found that the traditional investment model performed better than its dynamic counterpart. Marra and Carlson (1990) compared the expected utility model with and without risk in explaining the cropping pattern in Southeastern USA, and rejected the hypothesis that the riskiness of returns is important in the aggregate for certain states.

Finally, Alarcon *et al.* (1997) recently analysed the performance of three models: classical linear programming (LP), quadratic programming (following Baumol's formulation of risk<sup>1</sup>), and positive mathematical programming (PMP). The authors conclude first that the LP approach is not suitable to assess the impact of agricultural policy changes; secondly, that although the quadratic approach performs better than the LP, they do not allocate great importance to the inclusion of risk in the modelling approach for the type of farms analysed, and thirdly, that the best performance is offered by the PMP model.

# **Objectives**

This paper has two objectives. First, to test the performance of the mathematical models by their ability to reproduce the observed crop distribution of farms following the implementation of the 1992 reform of the Common Agricultural Policy (CAP). Second, once the best model has been identified, to assess its performance under limited data, i.e. average data instead of time series from individual farms.

# 2. Source of data

In order to take into account both farms' agro-characteristics and farmers' behaviour we collected data on crop distribution and gross margins of eighteen farms from an accounting firm for a period of five years:

- 1988/89 to 1991/92: base period used to obtain recent yields, costs, average gross margins and rotation practices.
- 1992/93: farmers' cropping patterns for purposes of prediction. These data corresponded to the first year of full implementation of the 1992 CAP reform.

We selected a limited period of five years in order to eliminate any structural adjustments in the production capacity of the farm, thus enabling the mathematical modelling approach to adequately reproduce short-term behaviour.

<sup>&</sup>lt;sup>1</sup> The expected gross margin is maximized once the probability of a minimum gross margin exceeds  $(1-\alpha)$ . See Baumol (1963).

# Area and period of study

The eighteen irrigated farms are located in the County of Seville in the Guadalquivir Valley in Southern Spain, with a typical Mediterranean climate. The choice of irrigated rather than rainfed land was made due to the much more wide range of crops available to the first type of farm. The arable crops grown by a typical farm in this area consist mostly of sunflowers, cotton, cereals and vegetables. The following table groups all the arable crops grown in the County.

#### HERE TABLE 1

As the above table shows, after the first year of full implementation of the CAP reform (1993) the percentage of sunflower increased markedly, whereas cereals and cotton fell in importance. The eighteen farms of this study presented similar patterns, as summarised in the following table.

# HERE TABLE 2

In these farms, following the implementation of the policy reform, there was a clear reduction in cotton and cereals, and an increase in sunflowers. Table 3 presents the average crop distribution of each farm during the three-year period immediately prior to the CAP reform, and its size in hectares.

# HERE TABLE 3

#### 3. Policy implications of the 1992 CAP Reform

As is well known, the 1992 CAP reform partially shifted price support to income support by means of direct payments to farmers (Josling, 1994; Swinbank, 1997; Ingersent and Rayner, 1999). In order to participate in the new scheme farmers were required to set aside 15 per cent of their arable land<sup>2</sup>, without the possibility of producing any crop for human or animal consumption on set-aside land. In return, they received a compensatory payment based on the area of cereals, oilseeds, protein crops and set-aside land.

The estimated market price for cereals in 1992/93 was 128.32 ecus/tonne<sup>3</sup> (147.98 euro/tonne). For sunflowers, a price of 163 ecus/tonne<sup>4</sup> was expected. These two prices were used as farmers' price expectation in the simulations. We thus obtained the expected cereal and sunflower gross margins by multiplying the previous prices by the average yield, minus the average variable costs of the individual farm, plus the area payment. The other crop gross margins were set as the average of the previous four years for each farm.

As a result of the CAP Reform of 1992, the gross margins of cereals, oilseeds and protein plants (COP) were changed following the expected fall in the commodity market price and the increase obtained from the new area payments.

# 4. Methodology

#### Comparison of models

In order to compare the predictive ability of each model the following procedure was applied to each farm:

- 1. We expressed the observed crop distribution through the five years as fractions of unity. The sum of decisional variables (crop activities) to optimize also equalled one.
- 2. We determined the CAP, resource, market and rotational constraints that applied to all models.
- 3. For all farms the same crops were considered as the decision variables. If a farm did not grow a particular crop, the average crop gross margin, and other parameters such as variance when required, of all farms during the base period were used as alternative activity in the programming model. Rice was excluded since it is not interchangeable with the other crops.
- 4. We optimized the objective function.
- Finally, we compared the optimum with the observed crop distribution of the 1992/93 year. The accuracy of the model prediction was measured as the sum of the absolute deviations between the observed and the optimum crop area allocation;

 $<sup>^{2}</sup>$  Those farmers that exceeds an area corresponding to 92 tonnes of cereals in his yield region (i.e. 20 ha on EU average).

<sup>&</sup>lt;sup>3</sup> Intervention price= 115.49 Ecus/ton; Reference price= 128.32 Ecus/ton; Threshold price= 172.74 Ecus/ton (Junta de Andalucia, 1994).

<sup>&</sup>lt;sup>4</sup> Commission of the European Communities (1992).

mathematically:  $d = \sum_{i} |O_i - M_i|$ , where  $O_i$  is the observed land allocation of crop *i* and  $M_i$  is the model prediction<sup>5</sup>.

# Constraints of all models

Since all the farms in the study are located close to each other they are relatively homogeneous in terms of land quality and the availability of other resources. Therefore the same constraints were applied to all models and farms. The differences in predictions of the models are thus explicable by the objective function and not by the constraints set.

Four types of constraints were applied in the models:

- Rotational constraints (sequence of crops): This prevents the introduction of sequences of crops that conflict with traditional practices, and was based on the available time series of the farms and an extensive survey<sup>6</sup> of the same area. Cotton was limited to 0.50 (of a farm area of 1.00). Alfalfa, a non-annual crop, was limited to m/(m+n)·total area = 0.57, where "m" represents the number of years of the crop on the land and "n" the number of years before repeating sowing on the same plot. Similarly, asparagus was limited to 0.58.
- 2. *Resource constraints*: The total crop demand for water could not exceed the resource availability for an average year. Total crop area equalled unity (land constraint), and no rented land was allowed.
- 3. *Policy constraints* (Common Agricultural Policy CAP): This limited the maximum area of sugar beet to the maximum observed area of the four-year base period.
- 4. *Market constraints*: In order to avoid biased solutions in models without risk consideration toward vegetables (asparagus, potatoes and tomatoes), with higher gross margins but riskier, the optimum was limited to, on the basis of a survey of 215 farmers in the same area (Arriaza, 2000), one and a half the maximum observed percentage of these crops during the base period. This constraint included risk via the constraint set rather than making it explicit in the objective function (Wheeler and Russell, 1977).

<sup>&</sup>lt;sup>5</sup> For example, a farm with the following observed crop distribution: cotton 0.40, wheat 0.30 and asparagus 0.30 (the sum equals one), and a predicted optimum plan: cotton 0.55, wheat 0.10 and asparagus 0.35, would imply d = |0.40-0.55| + |0.30-0.10| + |0.30-0.35| = 0.40.

<sup>&</sup>lt;sup>6</sup> Survey of 215 farmers belonging to three communities of irrigators, where the eighteen farms of this paper are located, selected by stratified sampling and carried out in 1998 (Arriaza, 2000).

#### Description of the selected models

The range of models included a number of well-known linear programming approaches to agricultural policy analysis. The various optimizing procedures considered one criterion (profit), two (profit and risk) or three (profit, risk and labour). The models studied were:

1. <u>Expected profit maximization</u> (EPM). The total gross margin of the farm is maximized subject to the above constraints. This simple model, which was widely used in the past, incorporates risk by assuming that farmers maximize *expected* profit (Hazell and Norton, 1986, p.11; Selley, 1984, p.54).

2. <u>Additive utility function with two objectives: maximization of total gross margin and</u> <u>minimization of total qualitative risk</u> (UQR). The additive utility function has been widely used to model farmers' decisions when one of the criteria involved is uncertainty. The ranking of alternatives is obtained by adding contributions from each objective. Since attributes are measured in terms of different units, normalisation is required to allow addition. The weighting of each attribute expresses its relative importance. Mathematically, its simplest form is:

$$U_i = \sum_{j=1}^n w_j r_{ij}$$
,  $i=1, ..., m$ 

where  $U_i$  is the utility value of alternative *i*,  $w_j$  is the weighting of attribute *j* and  $r_{ij}$  is the value of attribute *j* for alternative *i*.

Fishburn (1982) presented the mathematical requirements for assuming an additive function, while Massam (1988) and Hardaker *et al*, (1997) explained them from a practical point of view. An example of verification of the conditions for assuming an additive formulation can be found in Keeney and Nair (1977).

Although these conditions are somewhat restrictive, Edwards (1977) and Farmer (1987) have shown that the additive function yields extremely close approximations to the hypothetical true function even when these conditions are not satisfied. Hwang and Yoon (1981, p.103) and Huber (1974) coincided in claiming that while an additive utility function will not accurately specify the farmers' true utility function, it will generally serve reasonably well to

discriminate between acts in much the same way as would a more correct but far more complicated non-additive function.

We adopted a non-interactive procedure to elicit a surrogate of the farmer's true utility function as developed by Sumpsi *et al.* (1996) and Amador *et al.* (1998). Briefly, the methodology used to obtain the utility function is as follows:

- 1. Determine a tentative set of objectives aimed for by the farmers.
- 2. Obtain a pay-off matrix in which element a<sub>ij</sub> represents the value achieved by the *i*-th objective when the *j*-th objective is optimized.
- 3. Using goal programming, calculate the weight of each objective that minimizes the distance from the observed value of the same objective.
- 4. Normalise the previous weights dividing by the range of their respective objectives (in the pay-off matrix, the best and worst values).
- 5. Compose the additive utility function using the normalised weights.

In this model (UQR) and the next (UVR), three objectives were considered: maximization of total gross margin, minimization of risk and minimization of labour. The UQR and UVR models differ in the way in which they formulate risk:

- The UQR model computes the total risk index of a crop plan as R=∑x<sub>i</sub> q<sub>i</sub>, where x<sub>i</sub> is the land allocation of crop i and q<sub>i</sub> is a qualitative risk index obtained in the above-mentioned survey, with the following values ordered by increasing riskiness: 0 (set-aside), 1 (sunflower), 2 (wheat), 3 (maize and alfalfa), 4 (sugar beet and rice), 5 (cotton), 6 (asparagus and tomatoes), and 7 (potatoes).
- The UVR model measures risk in terms of the variance of the average crop gross margins of all farms. We used the yields and costs of the period 1988/89 to 1991/92 and the new COP prices after the 1992 CAP reform to estimate future crop gross margins, and then calculated the variance-covariance matrix which was the same for all farms. This procedure takes into account the reduction of risk via direct payments, since these area payments are not included in the crop gross margins when the matrix is calculated.

In both models, the weight attached to the minimization of labour, following this elicitation procedure, is zero. Hence, only two objectives are included in the utility function: the maximization of the total gross margin and the minimization of risk.

3. <u>Additive utility function with two attributes: the total gross margin and the variance of the total gross margin</u> (UVR). The weighting of each attribute in the additive utility function is calculated following the methodology outlined in the description of the previous model. Two applied studies of irrigated farms that employed this model, one in the same area and the other in Northern Spain, can be found in Arriaza *et al.* (2001) and Gómez-Limón *et al.* (2002), respectively.

4. Expected profit maximization limited to the maximum total qualitative risk index of the base period (EPQ<sub>max</sub>). Like Model 1, this model maximizes the farm's expected profit but limits the qualitative risk index. This index,  $R=\sum x_i q_i$ , (see Model 2, UQR, above) is calculated for each of the four years of the base period; the model then maximizes the expected profit subject to a qualitative risk index that is lower than the maximum value achieved by the four indices.

5. Expected profit maximization limited to the minimum total qualitative risk index of the base period ( $EPQ_{min}$ ). This is a more conservative model than the previous one. In this model the qualitative risk index does not exceed the *minimum* of the four indices.

6. <u>Safety-first model</u> (SFM). In this model the worst gross margins of each crop during the base period are added to form the minimum total gross margin (TGM<sub>min</sub>). Once TGM<sub>min</sub> exceeds a certain amount, fixed at 700 euro/ha<sup>7</sup>, the model maximizes the expected total gross margin. This approach guarantees the farmer a minimum income (Hazell and Norton, 1986, p.100; Robison *et al.*, 1984, p.19).

7. <u>Weighted goal programming</u> (WGP). The model minimizes the deviation of each objective from the set of targets defined by the farmers. The unwanted deviations (either positive or negative or both) are weighted, indicating the importance attached to each objective. To allow for summation, the deviations are normalised by dividing them by the expressed level of the target (Romero and Rehman, 1984; Rehman and Romero, 1993; Tamiz *et al.* 1998).

The target for the farm total gross margin is set at its maximum obtained value during the base period, whereas the sum of the standard deviations of the crop gross margins (risk measure)

<sup>&</sup>lt;sup>7</sup> This amount reflects an average hiring-out land price in the area of study (Arriaza, 2000).

and total labour are set at their minimum values. The same observed values are used to normalise the deviations. Mathematically, the objective function is:

$$\min Z = w_1 \frac{n_1}{TGM_*} + w_2 \frac{p_2}{R_*} + w_3 \frac{p_3}{L_*}$$

where  $w_i$  is the importance attached to objective *i*,  $n_i$  and  $p_i$  are negative and positive deviations from the targets,  $TGM_*$  is the maximum TGM of the base period, and  $R_*$  and  $L_*$  are the minimum risk and labour, respectively, of the same period. Risk is calculated as:  $R=\sum x_i \cdot s_i$ , where  $x_i$  represents area of crop *i* and  $s_i$  is the standard deviation of the gross margins of the crop *i* during the base period.

Whereas in Models 2 (UQR) and 3 (UVR) the weights attached to each criterion (profit, risk and labour) are calculated from the observed crop distribution of each farm, in this approach (WGP) we used the same weightings for all farms, as calculated from a survey of 215 farmers in the same area (Arriaza, 2000).

The procedure involves direct interaction with the decision-maker (Ziont and Wallenius, 1976; Barnett *et al.*, 1982; Gass, 1987). Farmers were asked to rank their objectives, with the following results: first, maximization of profit, second, minimization of risk, third, minimization of labour, and fourth, others (mainly rotational requirements). Scaling each objective from 4 to 1 the sum gives a measure of relative importance, as presented in Table 4:

#### **HERE TABLE 4**

Since the weighting of the "other" objectives is very small (3 per cent) the objective function Z is limited to three criteria and their deviations are weighted as follows:  $w_1=0.57$ ,  $w_2=0.28$  and  $w_3=0.15$ .

Although the weights are the same for all farms, the targets are specific to each one. Thus, the WGP approach includes the individual preferences of each of the eighteen farms through their targets, set at the best result of the four-year base period.

8. <u>Positive mathematical programming</u> (PMP). This method maximizes expected total gross margin in a way that reduces crop yields, and therefore crop gross margin, as the optimum allocation of crop area exceeds the observed crop area. The result is a self-calibrating model (Howitt, 1995; Júdez *et al.*, 1998).

#### 5. Performance of the models

Table 5 summarizes the results ordered by farm size and model performance. The performance index, i.e. the sum of the absolute deviations between the predicted and observed crop distributions, can range from 0.000 (best performance) to 2.000 (worst performance).

#### **HERE TABLE 5**

As the above table shows, the two best models incorporate risk in the optimization procedure on a qualitative basis. The first,  $EPQ_{min}$ , maximizes expected profit constrained to a qualitative risk index lower than the minimum observed value of the index during the fouryear base period. This approach, however, could be used even when only one year is available, with the added advantage of the limited amount of information required for risk modelling: only a qualitative ranking of the relative riskiness of crops.

The UQR model, like the previous one, requires the qualitative riskiness ranking of all crops. However, this approach incorporates risk in the objective function together with the expected profit. Likewise, the utility function can be elicited from only one year's data.

Although the PMP approach performs well, it has the limitation of excluding crops that are not present in the base year. However, if the excluded crops are not regarded as a real alternative for the farmer, this approach yields satisfactory predictions.

Each of the other models has its own shortcomings: WGP demands interaction with the decision-maker in order to obtain the weight of each objective; UVR requires a time series of crop gross margins; SFM is too conservative and, in general, not particularly suitable for

farmers in the developed world; finally, EPM does not capture the risk dimension embedded in the farmer's decision-making process and results in a poor prediction of the policy impact.

Finally, the column before farm size, AVE, represents the result of a naive model that assumes that farmers do not alter their behaviour after the change in agricultural policy. If such is the case , the predicted cropping pattern remains the same as during the three-year period (88/89-90/91) with no area payments.

#### 6. Performance of the EQR<sub>min</sub> model under average data availability

Since adequate time series for each crop and farm are not easy to find, one question remains unanswered: is the good performance of this model dependent on the availability of specific farm data? This section deals with the issue and analyses the predictive ability of the model in the case of access only to average data. We use only one year of observed crop distribution (so we call it  $EQR_{obs}$  instead of  $EQR_{min}$ ) and average crop gross margins. The expected crop gross margins are equal to the average of the previous four-year period, except for the crops affected by the 1992 CAP reform (sunflower, wheat, maize and set-aside). The following table summarizes the information needed for the modelling exercise.

#### HERE TABLE 6

These results show that the model performs equally well using the total risk index for only one year instead of the minimum of a period (0.59 instead of 0.55). The same model, but without the constraint of a limited total risk index, yields a performance d-index equal to 1.20.

#### 7. Conclusions

This paper presents a simple modelling approach (EQR<sub>obs</sub>) that, in this case study, outperforms other modelling alternatives. It yields the best results in terms of predictive capacity to the 1992 EU agricultural policy reform. The model maximizes the expected total gross margin subject to a maximum qualitative total risk index. In terms of data requirements, apart from the observed crop distribution and average crop gross margins, only a qualitative ranking of relative crop riskiness for risk modelling is needed.

A second approach with good predictive properties (UQR) elicits a utility function with two attributes: the expected total gross margin and, like the previous model, the qualitative risk index. One of it's the most attractive properties of this model is that it does not require any interaction with the decision-maker to elicit a surrogate of the farmer's utility function. The positive mathematical programming (PMP) model also produces adequate predictions, although this model does not incorporate crops that are not included in the base year.

According to these results, the predictive ability of the traditional profit maximization model is very low. In our opinion, this indicates the necessity of including at least profit and risk as the two criteria in agricultural modelling exercises that aim to successfully predict farmers' responses to policy changes.

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WORD COUNT (including tables): 5,645

	Cereals	Oilseeds	Cotton	Other indust.	Vegetab.	Forage	Others	Total (ha)
88/89	38.8%	15.0%	19.6%	8.7%	13.3%	3.5%	0.9%	142,319
89/90	37.8%	15.2%	20.7%	10.0%	11.9%	3.6%	1.0%	152,877
90/91	38.2%	15.0%	20.4%	9.8%	11.9%	3.8%	0.8%	156,548
91/92	30.2%	17.1%	17.6%	13.1%	12.9%	3.9%	5.2%	152,181
92/93	18.7%	45.7%	8.2%	11.4%	11.5%	4.0%	0.5%	147,699

Table 1. Irrigated arable crops in the county of Seville during the period of study

Source: 1T, crop distribution by municipalities. Junta de Andalucía.

	Cotton	Wheat	Maize S	unflower	S. Beet V	egetables	Rice A	Alfalfa S	Set-aside
88/89	23.4%	6.7%	16.8%	28.5%	6.9%	13.2%	4.5%	0.0%	0.0%
89/90	24.7%	6.9%	6.9%	32.1%	6.7%	18.7%	4.0%	0.0%	0.0%
90/91	17.1%	6.9%	14.4%	23.0%	6.0%	24.2%	4.0%	0.0%	4.4%
91/92	18.1%	5.9%	1.9%	36.3%	5.8%	23.5%	2.0%	1.6%	4.9%
92/93	13.1%	1.3%	0.8%	52.0%	1.2%	20.6%	0.0%	1.6%	9.4%

Table 2. Average crop distribution by year of the eighteen farms in the study

Source: Accounting firm database

Farm	Cotton	Wheat	Maize	Sunflow	S. Beet Aspar.	Potato Tomat	Rice Set-aside Size (ha)
F1	75.0%			25.0%			21
F2	11.1%		44.4%	44.4%			30
F3	33.3%		16.7%	16.7%		16.7% 16.7%	32
F4	17.4%		27.3%	12.9%		25.8% 16.7%	33
F5			50.0%	50.0%			40
F6				3.6%	92.8%	3.6%	45
F7	56.8%		37.4%		6.2%		48
F8	42.2%			36.9%	20.8%		67
F9	18.7%			9.3%			72.0 75
F10		47.5%		52.5%			90
F11	30.0%	15.9%	4.8%	30.0%	13.0%		6.3% 90
F12	21.9%		8.9%	32.8%	7.4%	17.7% 11.3%	104
F13	20.7%	9.1%		31.9%	38.3%		112
F14	13.1%	24.9%		29.3%	23.5%		9.2% 135
F15	7.8%	13.5%		62.6%		6.7%	9.4% 184
F16	3.7%	7.9%	7.1%	22.9%	10.4% 4.1%	12.0% 32.0%	188
F17	34.8%		14.0%	28.6%	6.6%	8.0% 7.3%	0.8% 303
F18	14.8%		23.5%	18.2%	31.9%	4.6% 6.1%	0.8% 310
Aver.	22.3%	6.6%	13.0%	28.2%	6.3% 7.9%	4.9% 5.4%	4.0% 1.5% 106

Table 3. Average crop distribution and size of the eighteen farms during the three-year period before the CAP reform

Source: Accounting firm database

	Weighted importance							
Objective	Scoring	All four objectives Without of	ther objectives					
Max. profit	715	0.55	0.57					
Min. risk	346	0.27	0.28					
Min. labour	196	0.15	0.15					
Other objectives	38	0.03	-					
Total	1,295	1.00	1.00					

Table 4. Ranking and weights of farmers' objectives

Source: Survey of 215 farmers in the area under study (Arriaza, 2000)

Farm	EPQ <sub>min</sub>	UQR	PMP	WGP	EPQ <sub>max</sub>	UVR	SFM	EPM	AVE	Size (ha)
F1	0.04	0.04	1.00	0.26	0.04	0.70	0.04	0.04	1.50	21
F2	1.33	1.50	1.31	0.76	1.33	1.33	2.00	2.00	1.11	30
F3	1.01	1.22	0.75	1.20	1.19	1.75	1.22	1.22	1.00	32
F4	0.29	1.07	0.08	0.92	1.50	1.07	1.50	1.50	0.77	33
F5	0.13	1.10	0.04	1.41	1.10	1.10	1.10	1.10	1.00	40
F6	0.70	0.33	0.67	0.74	0.40	2.00	0.33	0.33	0.59	45
F7	0.90	1.02	0.17	1.01	1.02	0.98	1.02	1.02	0.75	48
F8	0.44	0.44	1.00	0.55	0.44	0.44	0.44	0.44	0.84	67
F9	1.14	2.00	0.03	0.72	1.86	0.51	2.00	2.00	0.72	75
F10	0.67	0.68	0.76	0.90	0.68	1.09	1.02	0.68	0.74	90
F11	0.05	0.05	0.03	1.11	0.05	0.05	0.05	0.05	0.56	90
F12	0.66	0.67	1.08	0.37	0.67	1.15	0.85	0.85	0.89	104
F13	0.69	0.04	1.87	0.33	1.00	0.04	0.15	1.00	2.00	112
F14	0.04	0.04	1.00	0.66	0.04	0.04	0.04	0.04	0.81	135
F15	0.14	0.95	0.71	1.09	0.68	0.95	1.13	1.13	2.00	184
F16	0.25	0.25	0.94	0.37	0.68	0.24	1.00	1.00	0.29	188
F17	0.82	0.63	1.32	0.61	0.98	1.13	0.98	0.98	0.41	303
F18	0.56	0.75	0.80	1.00	0.41	0.69	0.75	0.75	0.51	310
Average	0.548	0.710	0.753	0.778	0.782	0.848	0.868	0.897	0.916	106

Table 5. Performance index of the selected models to predict the impact of the 1992 CAP reform

 $EPQ_{min}$ = Expected profit and min. qualitative risk index of base period; UQR= Utility function with expected profit and qualitative risk index; PMP= Positive mathematical programming; WGP= weighted goal programming;  $EPQ_{max}$ = Expected profit and max. qualitative risk index of base period; UVR= Utility function with expected profit and variance-covariance matrix; SFM= Safety-first model; EPM= Expected profit maximization; AVE= Average crop distribution of base period.

	Cotton	Wheat	Maize	Sunfl	S.Beet	Aspar	Potato	Tomat	Rice	Alfalf	S.asid	Total
Crop distribution of the last year <sup>1</sup>	299	137	213	380	135	141	116	231	54	0	101	1805
Average crop gross margin <sup>2</sup>	1038	399	619	544	537	756	1558	1137	1398	355	0	
6 Qualitative crop 6 risk index 6 Observed area*	5	2	3	1	4	6	7	6	4	3	0	
risk index	1495	273	638	380	540	846	809	1383	216	0	0	6579
Expected gross margin	1038	445	687	776	537	756	1558	1137	1398	355	279	
Doptimum area*	2426	0	0	649	0	0	1213	2075	216	0	0	6579
6 Optimum crop 6 distribution 7 Observed crop	485	0	0	649	0	0	173	346	54	0	97	1805
Observed crop	236	23	14	939	22	85	123	163	0	29	170	
Optimum - bobserved area	249	23	14	289	22	85	50	182	54	29	72	
$\frac{a}{a}$ abs.diffenreces (d)	0.14	0.01	0.01	0.16	0.01	0.05	0.03	0.10	0.03	0.02	0.04	0.59

Table 6.  $EQR_{obs}$  performance under limited data availability

<sup>1</sup> Hectares; <sup>2</sup> euro/ha

Nom du document : 124-arriaza-rtf2 Text and tables Dossier : C:\Documents and Settings\gilles\Bureau\EAAE C:\Documents and Settings\gilles\Application Modèle :  $Data \\Microsoft \\Modèles \\Normal.dot$ COMPARATIVE PERFORMANCE OF SELECTED Titre : Sujet : Auteur : Manuel Arriaza Mots clés : Commentaires : Date de création : 15/02/2002 11:01 N° de révision : 3 Dernier enregistr. le : 07/03/2002 11:05 Dernier enregistrement par : GILLE Temps total d'édition : 2 Minutes Dernière impression sur : 07/03/2002 19:59 Tel qu'à la dernière impression Nombre de pages : 20 Nombre de mots : 5 201 (approx.) Nombre de caractères : 29 647 (approx.)