Improved Program Planning Approaches Generates Large Benefits in High Risk Crop Farming

– A Profitable Application of Time Series Models and Stochastic Optimization –

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Abstract

This paper examines whether there is room for the improvement of farm program decisions through the incorporation of mathematical optimization in the practical planning process. Probing the potential for improvement, we investigate the cases of four German cash crop farms over the last six years. The formal planning approach includes a systematic time series analysis of farm-specific single gross margins and a stochastic optimization model. In order to avoid solutions that simply exceed the farmer's risk tolerance, the apparently accepted variance of the observed program's total gross margin which represents an observable reflection of the individual farmer's risk attitude is used as an upper bound in the optimization. For each of the 24 planning occasions, the formal model is used in a quasi ex-ante approach that provides optimized alternative programs. The total gross margins that could have been realized *if* the formally optimized programs had been implemented are then ex-post compared to those that were actually realized. We find that the farmers could have increased their total gross margins significantly if - instead of using simple routines and rules of thumb - they had used the more sophisticated formal planning model. However, we also find that the superiority of formalized planning approaches depends on the quality of statistical analysis and the resulting forecasting model. Using our approach for practical decision support implies that farmers first specify their "own" production programs without the formal planning aid. Then, an alternative program can be provided which leads to superior expected total gross margins without exceeding the farmer's accepted total gross margin variance.

Keywords: production program planning, optimization, uncertainty, static distributions, stochastic processes

JEL classification: C1, C61, M11, Q12

Introduction

Optimization procedures (linear and quadratic programming) have been receiving a lot of attention in agricultural-economic research and teaching for several decades (cf. e.g. Heady and Candler 1958; Brandes 1974; Dent, Harrison, and Woodford 1986; Rae 1994; Hardaker et al. 2004). In the fifties and sixties of the last century, soon after the simplex algorithm was found by Dantzig in 1947 (cf. Dantzig 1963), agricultural economists started to use linear programming for farm planning. Early publications related to linear programming in agriculture either aimed at disseminating the mathematical knowledge by explaining the characteristics of the procedure (cf. e.g. Heady 1954; Boles 1955) or at pointing out its possible applications and general potential for farm management (cf. e.g. McCorkle 1955; Swanson 1961). As long as linear programming computer codes were not easily available, many efforts were made to reduce the structural complexity and size of the planning models. This concerned, for instance, the aggregation of production activities and the consideration of limited supplies and other constraints (cf. e.g. Huffman and Stanton 1969).

Soon, agro-economists also aimed to improve optimization approaches by accommodating risk (uncertainty)[1] in their models, either in the objective function or in the constraints. The first approaches include Chance Constrained Programming (cf. Charnes and Cooper 1959) or simple variant calculations and sensitivity analyses (cf. Dinkelbach 1969). While these early approaches to risk do not explicitly take account of probabilistic information in terms of distributions, later programming approaches, following Freund (1956), explicitly resort to the variance, thus generating quadratic optimization problems. Looking for more convenient ways of computation, considerable efforts were made to find linear programming approximations to the quadratic risk programming problem (cf. Hazell 1971; Thomas et al. 1972; Chen and Baker 1974; Tauer 1983; Okunev and Dillon 1988), the best known of which is probably Hazell's Minimization-Of-Total-Absolute-Deviation (MOTAD) programming.

[1] In this paper we use the terms "risk" and "uncertainty" synonymously, implying that there is probabilistic information regarding the random variables.

At the end of the eighties and the beginning of the nineties, both linear and non-linear programming computer codes became generally available. In spite of the necessary technical tools being at hand (for an overview cf. Patrick and DeVuyst 1995), it is surprising that optimization has nonetheless hardly been treated as a serious support for on-farm decision-making in the agricultural-economic literature since. Even though the capacity for solving planning problems in situations involving limited resources is well-known, agricultural economists have so far not engaged in significant empirical research that investigates the benefits that could be derived from using optimization models for practical decision support. With regard to teaching, Hanf (1991) even raised the question of whether valuable time at universities is wasted with linear optimization. Thus, optimization has predominantly remained confined to academic research.

The planning of the production program based on formal optimization procedures requires the explicit definition of the set of restrictions, and thus of the set of feasible solutions. Furthermore, in a risky environment, the variability of economic parameters and the individual risk attitude need to be considered. Otherwise, a formal determination of the production program that maximizes the individual decision-maker's objective function is not possible. Due to the empirical problems of quantifying individual risk aversion (cf. Jolly 1983; Just and Pope 2003; Hudson, Coble, and Lusk 2005), conventional optimization approaches under uncertainty do not usually provide a single optimal solution. They rather provide - as a result of variant calculations - so-called *risk efficient* (or stochastically efficient) combinations of expected profits and involved volatility. Although thus one avoids the need to exactly quantify individual risk-attitudes, it is still difficult to obtain the remaining real-life data that are needed in formal optimization models. This refers to capacity and crop rotation restrictions as well as to the time series of the single gross margins. But even if one disposes of the farm-specific raw data, an adequate statistical analysis and a consistent processing of probabilistic information and of correlations between relevant stochastic variables remains quite laborious.

Furthermore, statistical analysis may be error-prone due to questionable a priori presumptions. The simple fact that time series may exhibit trends, e.g., suffices to show that "static distribution models" - i.e. the recourse to the mean and variance of past values considered equal in weight - do not represent good forecasting models. Nonetheless, some well-known concepts dealing with risk in agriculture use this assumption. MOTAD-models (cf. Hazell 1971), e.g., resort to the historical distribution. This implies that observed values are given equal weight. The same applies to most expected-value-variance (EV-) models (cf. e.g. Robison and Barry 1987). In multivariate analysis underlying EV-models, static normally distributed variables are commonly assumed for computational convenience (cf. e.g. Hazell and Norton 1986).[2]

Recognizing the problem of simplistic probabilistic assumptions, Adams, Menkhaus, and Woolery (1980) as well as Musshoff and Hirschauer (2004) demonstrate that planning results in terms of strategies are very sensitive to how time series are statistically treated. Using trend-adjusted time series may be crucial, for instance. Adams, Menkhaus, and Woolery (1980, p. 19) consequently point out that "if researchers intend to use the E,V approach in providing decision making information to producers, care should be exercised in the choice of income and risk measures used." In contrast to a priori presumptions regarding a variable's randomness, explicit time series analysis can be seen as searching for the stochastic process (time series model) that reflects the true stochastic pattern of a variable's development over time (cf. Pindyck and Rubinfeld 1998). Nonetheless, until now, stochastic optimization models have hardly been based on stochastic processes as derived from explicit time series analysis.

Questioning the extra value of formal risk programming models, a widespread opinion is that farmers - in particular with regard to the recurrent program decisions in crop farming - make near-optimal choices based on experience, incremental learning and simple heuristics (cf. also Gigerenzer and Selten 2001). Hence, it is argued, they do not need to explicitly quantify planning assumptions such as differentiated crop rotation requirements, the risk associated with various production activities, and their individual risk aversion. In the past, many attempts have been made to assess the extra value of risk programming models by comparing the results of different formal (theoreti-

[2] Computational difficulties arising in the case of multiple, non-normally distributed correlated variables are, e.g., discussed in Buccola (1986), Preckel and DeVuyst (1992), and Sornette, Simonetti, and Andersen (1999).

cal) planning models (cf. e.g. Brink and McCarl 1979; Kingwell 1994; Pannell and Nordblom 1998). Most often, the results from deterministic optimization models are compared with those from risk programming models. Sometimes, the comparison includes different types of risk programming models. In this context Pannell, Malcolm, and Kingwell (2000) claim that the incorporation of risk and risk aversion in a planning model only causes marginal changes of the optimal results, thus not justifying the efforts associated with highly sophisticated risk modeling.

In fact, formal optimization has scarcely found its way into the agricultural practice, except for the determination of minimum-cost mixtures in the feed industry. As a rule, the use of optimization procedures is confined to agricultural-economic research concerning itself with the analysis and prognosis of how certain groups of farmers adapt to changed conditions of their economic environments (i.e. structural adjustments of the farming sector). Examples for such "policy models" are Positive Mathematical Programming (cf. e.g. Howitt 1995; Preckel, Harrington, and Dubman 2002), or Multi-Agent Models (cf. e.g. Balmann 1997; Berger 2001). Another application is efficiency analysis via Data Envelopment Analysis (cf. Coelli, Rao, and Battese 1998; Lissitsa and Odening 2005).

While an evolutionary economics perspective may explain how sectors at large adapt (quite well) to changes in their environments through selection and trial-and-error experiences of their members, the question remains whether there is room for improvement of on-farm decisions through more sophisticated formal planning. With a view to the apparently lacking support of risky farm decisions through formal planning models, the goal of this paper is to examine empirically whether (and, eventually, by how much) farmers' "intuitive" program decisions can be improved through adequate and manageable stochastic optimization procedures. We are the first, to our knowledge, to compare the results of theoretical models (normative benchmarks) generated in a quasi ex-ante analysis with empirically observed ones. Pursuing this goal, we can distinguish two sub-goals: first, we examine the suitability of different statistical models to represent the true stochastic pattern of random variables. In other words: we analyze the performance of different forecasting models in conjunction with risk programming models. Second, we identify a manageable method of how to obtain information regarding farmers' risk attitudes from observed behavior. Doing so facilitates a model-endogenous recommendation of *one* alternative production program.

Our exemplary empirical analysis is a case study looking at the performance of four German cash crop farms over a period of six years. For each of these 24 planning occasions, the formal planning model is used in a quasi ex-ante approach that provides optimized alternative programs. The total gross margins which could have been realized *if* the formally optimized programs had been implemented are then ex-post compared to those that were actually realized by the farmers. In other words: each farm in each year under consideration is subjected to a normative benchmark derived from the formal optimization approach. In brief, our empirical benchmark analysis has the following characteristics:

a. The uncertainty of the single gross margins (of wheat, barley etc.) is quantified through a statistical analysis of individual farm data. The resulting probabilistic information is used for the required one-year-ahead forecasts that are fed into the risk programming model. Three different variants of statistical analysis, and thus forecasting models, are tested: (1) estimation of "static distributions", (2) linear time series analysis, and (3) "unbiased" time series analysis which allows for linear *and* non-linear stochastic processes.

b. The farmer's subjective risk attitude is seen as finding one observable reflection in his choice of production program and his apparently accepted variance of the total gross margin. In the formal approach, this expression of his risk attitude is considered explicitly by the use of the observed variance as an upper bound in the optimization model.

c. For each of the 24 planning occasions, and for each forecasting models as derived from the three variants of statistical analysis (cf. a.), formal optimization models are run. These risk programming models maximize the expected total gross margin subject to each farm's limited resources and each farmer's admissible variance (cf. b.). Comparing the hypothetical results of the planning variants with the empirical ones facilitates preliminary conclusions regarding the general question of whether there is room for improvement of on-farm decisions. It also sheds light on the relative appropriateness of the different forecasts.

The remainder of the paper is structured as follows: the second section briefly describes the empirical data base. This includes the available resource supplies and the crop rotation requirements as well as the time series of the farm-specific single gross margins. In the third section, we describe the three variants of how the single gross margin time series are statistically analyzed. In the fourth section, we describe the formal optimization model and the procedure of the empirical performance analysis. We also relate our approach to conventional risk programming approaches. Section five presents the results of the performance comparison between the empirically observed and the formally derived alternative production programs. Finally, we provide conclusions in section six.

Database

We are considering four large cash crop farms in Brandenburg, North-East Germany. Farms 1, 2, and 3 are located about 50 km west of Berlin, and farm 4 is about 100 km north of Berlin. The average of their (quasi-constant) acreage over the last six years has been 729 ha (farm 1), 1 111 ha (farm 2), 1 210 ha (farm 3), and 175 ha (farm 4). Three workers are employed on farm 1, five on farm 2, four on farm 3, and one is on farm 4. The major production activities considered by farmers 1, 2, and 3 include winter and spring wheat, winter rye, winter and spring barley, winter canola, corn, and non-food canola or set-aside land. While having an otherwise similar crop mix, any spring crops are rejected by farmer 4.

For all farms, minor crops such as alfalfa, oil flax or peas are excluded from the performance comparison. These crops represent rather fancy activities than serious production activities. Their proportion is almost irrelevant on all farms. Sugar beets, while being a relevant crop, are not considered in the model either. Being profitable without question, they are known to be grown with the maximum possible production volume according to the quota allocated to each farm. Excluding both fancy activities and the most competitive crop from the model considerations does not impede the insight to be gained from the analysis. It only leads to a shift in the level of both the empirical and the optimized total gross margins and is therefore irrelevant for the performance comparison.

The farmers were interviewed with respect to the annual single gross margins that were obtained over the last six years and the factor endowment (human resources and farm land). We also inquired about the number of field working days, the maximum working hours per day, and the time required for the various activities in the critical seasons March/April, May/June, mid-July/mid-September, and mid-September/mid-November. Furthermore, the restrictions of the crop rotation (minimum and maximum proportions of the particular crops) were considered. We cross-checked the farmers' answers related to crop rotation by looking at the empirical crop proportions. This allowed us to correct some of the data gained from the interviews. The manager of farm 1 indicated e.g., that he would grow a maximum of 50 % wheat. However, looking at his production programs, one could detect that wheat was grown on up to 53.5 % of the acreage. Consequently, this figure is used as the restriction of the crop rotation in the optimization model.

Both yield and market risks are embedded in the single gross margins of each crop. Thus, farm-specific time series of single gross margins are needed to specify the probabilistic information relevant to each farmer for his program decision. In principle, in time series analysis, data sets should be as large as possible. However, due to the structural discontinuity at the beginning of the nineties (collapse of the centralized economy and transition to market economy), farm-specific gross margins of before 1992/1993 for farms located in the new federal states of Germany often contain ambiguous information or are not available at all. Hence, we construct proxies for the years 1980 to 1992. These proxies are site-specific single gross margins which are based on yields obtained on comparable soils and under comparable natural conditions in the old federal states of Germany and on West German price data (ZMP, several years; LSD Brandenburg 2003).

The time series available at the respective planning dates $t^* - 1$ comprise the years $t = 1980$ to $t^* - 1$. The considered planning dates $t^* - 1$ are 1998, 1999, 2000, 2001, 2002 and 2003. Thus, a farm-specific time series of 19 data is available for each crop at the first planning date "fall 1998".

For each of the following planning dates, the available time series increases by one year. For each single gross margin, year and farm, the forecasting models, described hereafter in detail, are used: (1) static distributions, (2) linear time series models, and (3) unbiased time series models.

Time Series Analysis

Forecasting Model 1: Assuming Static Distributions

Forecasting model 1 implies that one determines a static parametric distribution for each of the single gross margins. According to the Chi-Square, Kolmogorov-Smirnov and Anderson-Darling tests, the normal distribution cannot be rejected for any of the considered single gross margin time series (at a significance level of 5 %).[3] However, when compared to the normal distribution, Beta, logistic and/or triangular distributions show a slightly better match with the empirical distributions in some cases. In agreement with the standard approach (cf. Hazell and Norton 1986, p. 81), we nonetheless assume a normal distribution for all single gross margins.

Let GM_t^j denote the gross margin per unit of production activity j observed at time t. Then the assumption of a static normal distribution for a single gross margin can be described as follows:

$$GM_{t^*}^j = E\left(GM_{t^*}^j\right) + \chi_{t^*}^j = \frac{1}{N} \cdot \sum_{t=1980}^{1980+N-1} GM_t^j + \chi_{t^*}^j \text{, with } N = t^* - 1980 \tag{1}$$

The future gross margin $GM_{t^*}^j$ results from its expected value $E\left(GM_{t^*}^j\right)$ and a $N\left[0, \sigma_{t^*}^j\right]$-normally distributed random component $\chi_{t^*}^j$ (error term, white noise). For a static distribution, the expected value corresponds to the mean. The standard deviation of the error term $\sigma_{t^*}^j$ simply reflects the standard deviation of all observed values. We introduce notation (1) - even though it is rather unusual for simple distributions - on grounds of consistency with the notation for the stochastic processes described below.

[3] We use the MS-EXCEL Add-In BEST FIT to analyze which distributions are plausible for the single gross margins.

Forecasting Model 2: Assuming Linear Time Series Models

Allowing for stochastic processes implies that one examines the time-dependent pattern of random variables through time series analysis. Abstracting from discontinuities, a stochastic process represents the best assumption with regard to the variable's distribution at future points in time. Auto-Regressive-Integrated-Moving-Average models of the order *p*, *d* and *q* (ARIMA(*p*,*d*,*q*)-models) are linear time series models. Due to their flexibility, ARIMA(*p*,*d*,*q*)-models are used to represent a multitude of stochastic economic processes (cf. e.g. Pindyck and Rubinfeld 1998).

The ARIMA(*p*,*d*,*q*)-model that fits best to a particular times series can be determined with the Box-Jenkins test procedure (Box and Jenkins 1976). According to this test, an AR(*p*)-process results for all single gross margin time series in our exemplary analysis:

$$GM_{t^*}^{j} = E\left(GM_{t^*}^{j}\right) + \chi_{t^*}^{j} = \alpha_0^j + \sum_{u=1}^{p} \alpha_u^j \cdot GM_{t^*-u}^{j} + \chi_{t^*}^{j}, \text{ with } \sum_{u=1}^{p} \left| \alpha_u^j \right| < 1 \tag{2}$$

α_0^j denotes a constant, α_u^j denote the weight factors that need to be estimated for the last p observation values $GM_{t^*-u}^{j}$, and $\chi_{t^*}^{j}$ describes a $N\left[0, \sigma_{t^*}^{j}\right]$-normally distributed error term. It should be noted that the expected value as well as the error term can, and most often will, differ from the ones obtained with the static distribution model even if the same data are analyzed.

Forecasting Model 3: Allowing for Non-linear Time Series Models

Recent research emphasizes the importance of non-linear dependencies in time series (e.g. Chavas and Holt 1991; Wei and Leuthold 1998). Non-linearity cannot be identified with standard statistical procedures such as the Box-Jenkins test (cf. Box and Jenkins 1976) or the Dickey-Fuller test (cf. Dickey and Fuller 1981). These "conventional" tests presume a priori linearity. Hence, more sophisticated statistical methods are needed which do not predispose linearity, but which facilitate the unbiased identification of both linear and non-linear processes. Artificial neural networks, increasingly applied in the field of financial analysis for predicting stock prices and interest rates (cf. e.g. Bishop 1995; Haykin 1999), have the capacity to approximate both linear and non-linear relationships. The result of a neural network analysis, however, is always an “implicit” model; i.e. no mathematical formulation of the time series is provided.

The method of “heuristic self-organizing time series models” originally described by Ivachnenko (1983) offers an alternative for the identification and specification of non-linear stochastic relationships (cf. Farlow 1984; Mueller and Lemke 2003). Compared to neural networks, the big advantage of this method is that it provides a mathematical formulation of the time series. It facilitates an automatic specification of a time series model of “optimal complexity“ without the need for any a priori assumptions regarding the structure (dimension of the polynomial).

A special class of self-organizing algorithms is the so-called Group Method of Data Handling (GMDH). GMDH-algorithms combine the connectionistic approach to artificial neural networks with the classical method of regression. They generate general polynomial process models (cf. Mueller and Lemke 2003, p. 77):

$$\begin{aligned} GM_{t^*}^{j} &= \gamma_0^j + \sum_{u=1}^{p} \gamma_u^j \cdot GM_{t^*-u}^{j} + \chi_{t^*}^{j} \\ &\quad + \sum_{u=1}^{p}\sum_{v=1}^{p} \gamma_{u,v}^j \cdot GM_{t^*-u}^{j} \cdot GM_{t^*-v}^{j} + \sum_{u=1}^{p}\sum_{v=1}^{p}\sum_{w=1}^{p} \gamma_{u,v,w}^j \cdot GM_{t^*-u}^{j} \cdot GM_{t^*-v}^{j} \cdot GM_{t^*-w}^{j} + \ldots \end{aligned} \tag{3}$$

These polynomials consider up to p preceding values with different weights as well as non-linear terms, the potential number of which exponentially increases with the number of considered preceding values. Thus, the functional form of the polynomial may easily get quite large. Its general structure however, can be understood as an AR(p)-process (upper line) which is extended by a non-linear component (lower line).

Heuristic self-organizing time series models determine both the polynomial’s optimal dimension and its parameters through starting from a very simple model and gradually increasing in complexity. The program divides the data into a training data set and a test data set used for cross-validation. First, a multitude of model hypotheses are generated based on the training data set. Then these model hypotheses are evaluated on the basis of the test data set. The model of optimal complexity is found as soon as one detects an over-fitting of the training data. Over-fitting means that a further increase in the model's complexity results in white noise of the training data being structurally mirrored in the model. Consequently, the model's predictive power for the test data decreases.

In the present application a regression model - non-linear if appropriate - is automatically generated for each single gross margin by means of GMDH.[4] While the GMDH-model has the principal capacity to account for any distribution, we assume normally distributed error terms since the results of the Chi-Square, the Kolmogorov-Smirnov and the Anderson-Darlings tests show that the normal distribution cannot be rejected at a significance level of 5 %.

Optimization Model and Performance Analysis

Figure 1 illustrates and subsumes the methodical steps of data collection and processing that are needed to optimize the production program. As described above, data are collected for each year and farm. This concerns the realized single gross margins up to the planning date, the constraints such as acreage, labor and crop rotation requirements, the empirically observed production program, and the achieved single gross margins realized in the target year. Then the single gross margin time series up to the respective planning date are statistically analyzed. The resulting probabilistic information includes the correlations, variances, and expectation values of the single gross margins. These values are specified separately in each of the three variants of statistical analysis. Depending on the consequently differing model inputs, the optimization model, of which the general structure is described below, will thus provide three alternative planning variants for each target year and farm.

[4] We use the software KNOWLEDGEMINER for Windows.

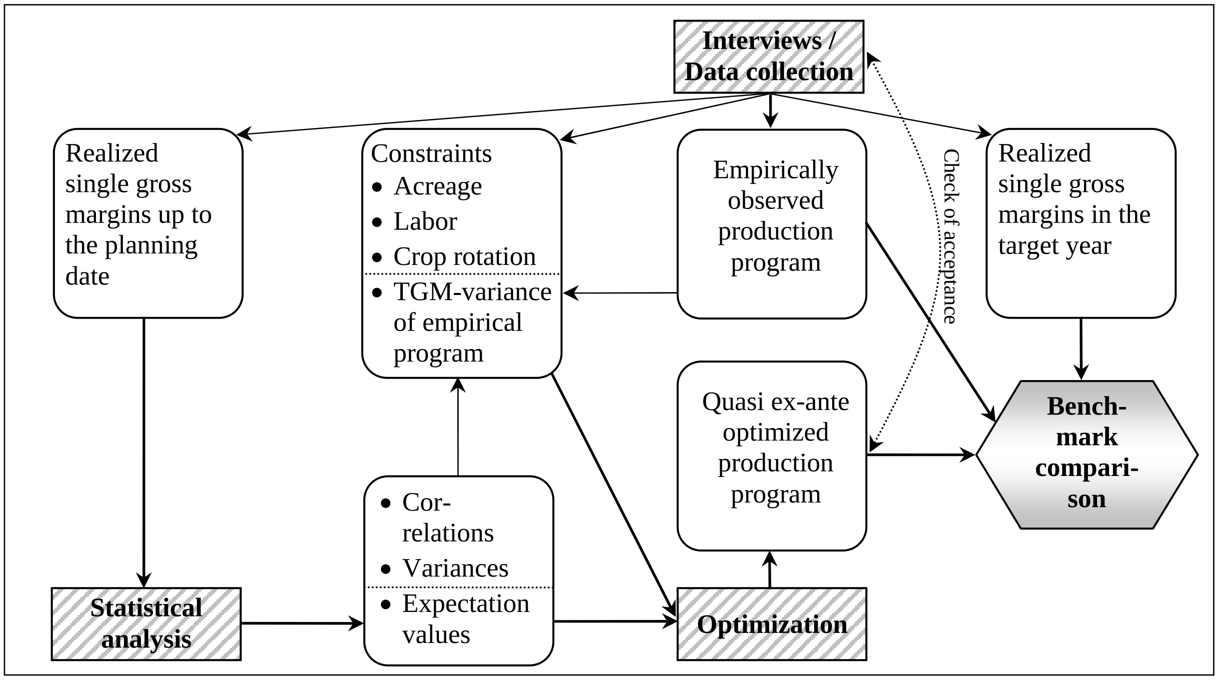

Figure 1. Synopsis of the methodological procedure

Optimization

The farm-specific constraints and the expectation values, variances and correlations of the single gross margins are fed into a quadratic optimization model. For each farm and planning date $t^* - 1$ (1998 to 2003), formally optimized alternative programs are determined according to expectations regarding the respective target year t^* (1999 to 2004). The optimization model can be described as follows:

$$\max_{x_{t^*}^j} E(TGM) = \sum_{j=1}^{J} E\left(GM_{t^*}^j\right) \cdot x_{t^*}^j$$

s.t.

$$\sum_{j=1}^{J} a_{t^*}^{i,j} \cdot x_{t^*}^j \le b_{t^*}^i, \quad i = 1,2,\ldots,I \qquad (4)$$

$$V \le V_{emp}$$

$$x_{t^*}^j \ge 0, \quad j = 1,2,\ldots,J$$

$E(TGM)$ denotes the expected total gross margin in the respective target year of the optimized production program. The objective function coefficients $E\left(GM_{t^*}^j\right)$ represent the expected gross margins per unit of production activity j. x_{t*}^{j} describe the levels of the production activities. b_{t*}^{i} denote the capacities (restrictions), and $a_{t*}^{i,j}$ represent the capacity requirements per unit of production activity. V_{emp} is the total gross margin (TGM-) variance inherent to the empirically observed production program. V, in contrast, denotes the TGM-variance of the optimized program. Using V_{emp} as an upper bound ensures that the reflection of the farmer's risk attitude as observed in his own choice of production program is taken into account in the optimization.[5]

The calculation of the variance is based on the results of the statistical analysis; i.e. the standard deviations and the correlation coefficients of the single gross margins (in the case of static distributions), and the standard deviations and the correlation coefficients of their error terms (in the case of stochastic processes). Since the J random variables (single gross margins) are additively combined, the TGM variance of the *empirical* production program V_{emp} can be calculated in a way analogous to a portfolio consisting of J asset positions (cf. Jorion 1997, p. 150):

$$V_{emp} = \sum_{j=1}^{J} \left(x_{t*,emp}^{j} \cdot \sigma^{j} \right)^{2} + 2 \cdot \sum_{j=1}^{J} \sum_{k<j}^{J} x_{t*,emp}^{j} \cdot \sigma^{j} \cdot x_{t*,emp}^{k} \cdot \sigma^{k} \cdot \rho^{j,k} \tag{5}$$

$\rho^{j,k}$ denote the correlation coefficients between the single gross margins j and k, or between their error terms. σ^{j} and σ^{k} describe the respective standard deviations. The correlation coefficient and the standard deviation are determined on the basis of the empirical data collected up to the particular planning date. $x_{t*,emp}^{j}$ and $x_{t*,emp}^{k}$ respectively, represent the weight (acreage) of the production activities in the farmer's empirically observed program. The TGM-variance of the *optimized* program V is to be determined in a way analogous to (5). One merely needs to replace the observed production levels $x_{t*,emp}^{j}$ and $x_{t*,emp}^{k}$ by the optimized production levels x_{t*}^{j} and x_{t*}^{k}. The TGM variance can only be derived analytically according to (5) if all single gross margins (in the case of static distributions) or all error terms (in the case of stochastic processes) are normally distributed. This being the case in the three variants of statistical analysis, we can do without numerical methods for determining the variance.

[5] For the sake of convenience, we omit the subscript t^{*} when referring to $E(TGM)$, V_{emp} and V. Nonetheless, they always correspond to the respective target year.

After the first optimization run, farmers are asked whether they accept the resulting programs and whether they consider them feasible and consistent with their personal preferences and the limited resource supplies. If necessary, supplementary constraints are added to the model. This is repeated until no further modifications are needed. This step by step procedure ensures that the optimized programs, while differing from the farmers' realized programs, are both feasible and acceptable for the real decision-makers.

Let us now subsume the essentials that are being considered by the optimization model (4):

- Only data that are available to the farmers at the respective planning dates $t^* - 1$ are used in the time series analysis and optimization; i.e., solely the single gross margins up to 1998 (1999, etc.) are assumed to be known when the production program for the target year 1999 (2000, etc.) is optimized.
- The optimization model considers the reflection of the farmer's individual risk attitude as observed in his own choice of production program by including the variance of the total gross margin from his actual program as an additional restriction. This facilitates individual decision support for farmers who differ in their risk aversion.
- While the efficiency challenge of farm management is far too large to be solved in a single-handed effort (or to be fully incorporated in a mathematical model of decision analysis for that matter), practical decision support subdivides the problem into manageable tasks (partial planning). Program optimization is a partial planning task. It considers the limited resource supplies and farm-specific single gross margins as "givens" and confines itself to identifying the optimal combination of production activities. It does not provide any answers regarding the best investment strategy (and thus the limited resource supplies at any one time) or regarding the best specification of activities (use of variable inputs such as fertilizer, plant protection, etc.) and marketing strategies (and thus the achievable farm-specific single gross margins).

Benchmark Comparison

We finally calculate the normative benchmark, i.e. the hypothetical total gross margin TGM which would have been realized in the target year *if* the optimized production program had been implemented:

$$TGM = \sum_{j=1}^{J} GM_{t*}^{j} \cdot x_{t*}^{j} \tag{6}$$

GM_{t*}^{j} indicate the actually realized single gross margins in the target year, and x_{t*}^{j} denote the planned proportions of crops as derived from the formal planning model. An ex-post comparison between the normative benchmark TGM and the farmer's actually realized total gross margin TGM_{emp} reveals whether an extra value could have been derived from using the formal planning model. TGM_{emp} is to be determined in a way analogous to (6). One merely needs to replace the optimized production level x_{t*}^{j} by the farmer's observed production levels $x_{t*,emp}^{j}$. Regarding the validity of the performance comparison, it should be emphasized that no informational advantage was accorded to the formal planner. The single gross margins realized in the target year are exclusively used for the final benchmark comparison.

A Brief Comparison with Conventional Quadratic Risk Programming

While bearing resemblance to conventional EV-models the proposed optimization approach under uncertainty exhibits some particularities: an EV-model represents a set of variant calculations each of which maximizes the expected value of the total gross margin for some predefined variance (cf. figure 2, left). Thus, a set of efficient combinations of variance and expected total gross margin are provided. If one assumes that the total gross margin is normally distributed, the EV-efficient set is also risk efficient, meaning that the solutions are second-degree stochastically dominant (Hardaker, Pandey, and Patten 1991). From a theoretical point of view, this assumption seems plausible due to the central limit theorem. This being confirmed according to the statistical tests in our application, we will deal with comparing this paper's approach to the general EV-approach hereafter.

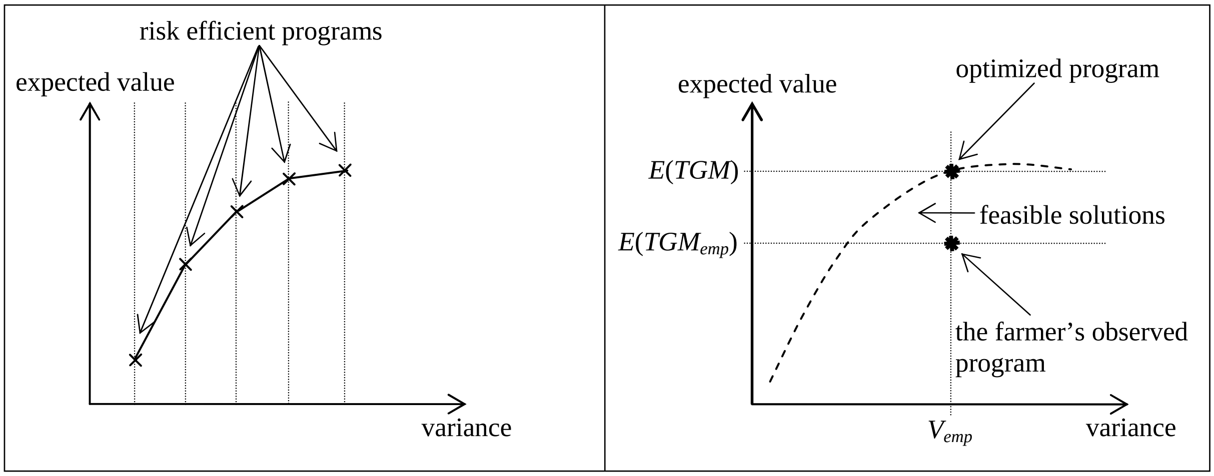

Figure 2. Classical procedure in the EV-model (left) vs. practical decision support (right)

For distinguishing our practical risk approach from the conventional method of handling unknown risk attitudes, we may refer to Hardaker, Pandey, and Patten (1991, p. 22) who describe the need for further research as "finding the best way of generating smaller and yet more relevant stochastically efficient solution sets." With regard to practical decision support, providing a solution *set*, however small, remains dissatisfying. If the farmer's individual risk attitude could be ascertained, the combination of risk and income that maximizes his utility could be identified endogenously from the risk efficient set. However, eliciting individual risk aversion is exactly the problem. That is, in conventional models the decision-maker is left alone with an exogenous choice to single out one combination of risk and income out of the many provided in the solution set.

Aiming at supporting practical decision-making, we maximize the expected total gross margin subject to the constraint of not exceeding the empirically observed willingness to accept risk. This means taking the variance of the total gross margin V_{emp} , inherent to the production program chosen by the farmer, as an observable, albeit incomplete, *reflection* of his subjective risk attitude (cf. figure 2, right). Realizing that the observed program is not only influenced by the risk attitude, we do not argue that this reflection represents the farmer's risk attitude completely. Nor do we presume that our procedure necessarily ensures the identification of the production program that maximizes the farmers' utility. Rather we focus on the manageability and applied usefulness of the approach which allows for a clear endogenous recommendation by reducing the efficient solution *set* to one *single* combination of variance and expected total gross margin. Technically speaking, we limit the set of feasible solutions to those yielding a higher or identical expected total gross margin at a lower or identical variance as the one previously accepted by the farmer. This is equivalent to limiting the formal search to an identifiable subset of solutions that are second-degree stochastically dominant compared to the farmer's own decision. While this subset does not necessarily include all second-degree stochastically dominant solutions, we are sure to increase (or at least meet) the farmer's *expected* utility compared to the one resulting from his routine program.

Discussion of Results

Comparison of Profitability

Until now, none of the decision-makers of the considered farms has been using formal optimization procedures to determine the production program. In fact, production planning is completely based on non-formal routines and intuition. Table 1 compares the average annual total gross margins realized by the farmers with those that could have been realized *if* the formally optimized programs had been implemented.

As an additional point of reference the first row of table 1 shows the hypothetical room for improvement (extra value) that would be generated if one had a "perfect forecasting model", i.e. a model, which exactly predicts the single gross margins in the respective target years. If such perfect information was available, the total gross margin could be improved by 15.9 % on an average over all farms and all years. Interpreting this figure one should note that a perfect prognosis is never available in reality because any time series contains unsystematic and unpredictable random errors. Hence, the figures of change depicted in the first row of table 1 are only a first hint that it is worthwhile examining the potential for improvement that might be generated by using formal procedures of statistical analysis and stochastic optimization.

Table 1. Average Annual Total Gross Margins (in €) of Realized and Optimized Production Programs

	Farm 1			**Farm 2**			**Farm 3**			**Farm 4**			**Sum over all farms**		
	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change
"Perfect forecasting model"	323 002	360 063	11.5 %	325 636	413 944	27.1 %	432 118	482 390	11.6 %	78 894	87 826	11.3 %	1 159 650	1 344 224	15.9 %
Approach 1: assuming static distributions	323 002	307 874	-4.7 %	325 636	360 656	10.8 %	432 118	420 384	-2.7 %	78 894	80 286	1.8 %	1 159 650	1 169 200	0.8 %
Approach 2: assuming linear time series	323 002	344 690	6.7 %	325 636	373 466	14.7 %	432 118	450 237	4.2 %	78 894	82 878	5.1 %	1 159 650	1 251 259	7.9 %
Approach 3: allowing for non-linear time series	323 002	349 028	8.1 %	325 636	374 385	15.0 %	432 118	446 061	3.2 %	78 894	82 619	4.7 %	1 159 650	1 252 093	8.0 %

Table 2. Annual Total Gross Margins (in €) of Realized and Optimized Production Programs Based on the Superior Approach 3

	Farm 1			**Farm 2**			**Farm 3**			**Farm 4**			**Sum over all farms**		
Target year t^*	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change	Empirical	Optimized	Change
1999	480 466	511 087	6.4 %	370 455	506 530	36.7 %	609 084	622 857	2.3 %	66 239	66 636	0.6 %	1 526 245	1 707 110	11.9 %
2000	339 544	347 890	2.5 %	295 934	315 797	6.7 %	462 911	479 697	3.6 %	76 887	80 250	4.4 %	1 175 276	1 223 634	4.1 %
2001	434 064	436 099	0.5 %	410 929	434 361	5.7 %	593 912	577 690	-2.7 %	74 546	77 211	3.6 %	1 513 451	1 525 360	0.8 %
2002	240 468	243 935	1.4 %	303 739	320 128	5.4 %	308 538	321 348	4.2 %	59 748	65 338	9.4 %	912 493	950 749	4.2 %
2003	168 913	274 723	62.6 %	255 150	326 454	27.9 %	263 096	285 644	8.6 %	59 389	63 460	6.9 %	746 548	950 282	27.3 %
2004	274 556	280 436	2.1 %	317 608	343 042	8.0 %	355 169	389 127	9.6 %	136 556	142 820	4.6 %	1 083 889	1 155 425	6.6 %
Average over all years	323 002	349 028	8.1 %	325 636	374 385	15.0 %	432 118	446 061	3.2 %	78 894	82 619	4.7 %	1 159 650	1 252 093	8.0 %

The rows 2 to 4 depict the extra value that is provided by formal planning based on the three different forecasting models described above. Only farm 2 could have improved its average annual performance significantly through the formal planning approach 1. The increase would have been quite low in farm 4, and on farm 1 and 3 the average annual performance would even have been inferior to that of the actual routine programs. While not being depicted, a look at the crop mix of farm 2 reveals that the optimized program suggests a sharp decrease of the proportion of corn. Farmer 2 has actually planted corn on 15 % of his acreage on an average whereas it is quasi irrelevant in the programs of the other three considered farms. Its comparative competitiveness being low, the 15 % proportion of corn on farm 2 must be interpreted as a serious planning mistake. It seems that the mistake is so gross that it could even have been attenuated through an optimization approach based on an ill-founded forecasting model. Despite its extraordinary (positive) effect on farm 2, the overall change of performance caused by approach 1 over all farms and all years is nearly zero. We must therefore conclude that a "standard" risk programming approach which incorporates risk through static distributions may even be inferior to routine decision-making of reasonably good farm managers.

Quite the reverse, that is, very encouraging results are found for the two other planning approaches (see the third and fourth row of table 1). The average total gross margin could have been improved significantly on all four farms if farmers had used formal optimization based on probabilistic information derived from systematic time series analysis: farmer 1 e.g., actually achieved an average total gross margin of € 323 002. Optimized production programs based on forecasting model 3 would have increased that amount to € 349 028. In other words: the average annual total gross margin in farm 1 could have been increased by 8.1 % (or € 26 026 per annum). In farm 2 the respective figures amount to 15.0 % (or € 48 749 per annum), in farm 3 to 3.2 % (or € 13 943 per annum), and in farm 4 to 4.7 % (or € 3 725 per annum).

Averaged over all farms, the potential for improvement compared to the farmers' routine programs amounts to nearly 8 % (7.9 % for approach 2, and 8.0 % for approach 3).[6] That is, even though much more effort went into the statistical analysis of approach 3, the results are only slightly superior to those derived from linear time series models. This might be interpreted as preliminary evidence that, with GMDH models which allow for non-linear time series, we have arrived at a stage of model sophistication where the marginal returns of increasing planning efforts sharply decrease.

Going beyond the consideration of averages, table 2 gives particulars of the performance of the most competitive planning approach 3 for each of the 24 planning occasions. The most essential results can be summarized as follows: first, the optimized programs derived from approach 3 outperform the empirical ones in 23 out of the 24 planning occasions. While not being depicted, it can be added that the same applies to approach 2. Approach 1, in contrast, outperforms the realized programs in merely 11 out of the 24 occasions. Second, being the odd exception, the total gross margin realized in the year 2001 by farmer 3 is higher than the one that would have been achieved with approach 3. At the planning date in the year 2000, however, the *expected* total gross margin of the optimized production program was 1.5 % higher than the one of the farmer's program. This underlines the well-known fact that in an uncertain environment an inferior decision may perchance result in higher profits, but that uninformed choices will not be superior in the long run.

Contrary to studies on production planning under uncertainty which compare the results of deterministic and stochastic (theoretical) planning models with each other, we explicitly use the results of formal optimization models as a normative benchmark for the results that have been empirically realized by farmers. On grounds of comparability with theoretical model comparisons, we additionally analyze a deterministic optimization model, i.e. we assume risk-neutral decision-makers. The deterministic model, which is based on the same forecasts as approach 3, is used as a second benchmark in our empirical performance analysis. Table 3 depicts the results.

[6] Additionally one could mention that the average total gross margin over all farms and years could be increased by 4.4 % if the formal planning approach had been based on a (linear) trend regression of the single gross margin time series (at a significance level of 5 %). In other words: optimization based on such a "rudimentary time series model" would still be inferior to optimization based on explicit time series analysis because a linear trend may be only *one* out of the many systematic components of a time series that should be considered.

Table 3. Performance Comparison of Different Planning Approaches

	Empirically realized program	Normative program		
		derived from approach 3	derived from deterministic approach	Change
Average annual expected total gross margin (€)	1 266 390	1 372 012	1 398 246	1.9 %
Average variance	$1.752 \cdot 10^{11}$	$1.737 \cdot 10^{11}$	$1.989 \cdot 10^{11}$	14.6 %
Ex-post average annual total gross margin (€)	1 159 650	1 252 093	1 267 844	1.3 %

Our best risk programming model (approach 3) and the deterministic optimization model yield similar average expected total gross margins (sum over all farms), differing only by 1.9 %. Their difference is even less if one looks at post at the total gross margins that would have actually been achieved with the respective programs. While this may be prima facie amazing, premature interpretations should be avoided. In any investigating as to whether formal programming models open up room for improvement of practical planning, the following essentials need to be considered:

First, even though the expectation values may be similar, the programs derived from a deterministic model may not be acceptable to risk-averse farmers. In our case we found, e.g., that the average total gross margin variance is 14.6 % higher than that of the risk programming model which considers the empirically observed reflection of the farmer's risk attitude (i.e. the empirical variance). Graphically speaking one would have to conclude that the EV-frontier is relatively "flat" in the relevant area, allowing for a significant decrease of volatility through a minor decrease of the expected total gross margin. Even for farmers with low risk aversion the program derived from the risk programming model might thus be superior. While not knowing farmers' precise risk premiums, this difference in variance provides evidence that relevant planning occasions exist where the consideration of risk is important. This finding is in contradiction to Pannell, Malcolm, and Kingwell (2000, p. 72) who conclude that the "consideration of complexities such as risk aversion […] does not greatly affect farmer welfare."

Second, the comparison of different *theoretical* models does never facilitate conclusions regarding the potential for improvement of real-life decision making. Instead, the hypothetical performance of the formal planning model needs to be compared with the empirical performance that farmers realize through their own routine decisions. That is, one really needs to compare the first and the second column of table 3. As already mentioned, this empirical performance comparison reveals that we were able to suggest a program which is acceptable to the farmers without doubt and which facilitates an average 8.0 % increase of the total gross margin over the of 24 planning occasions considered (see table 1 and table 2 for the details).

Comparison of Production Programs

Table 4 provides a rough characterization of production programs by comparing the farmers' average crop mix over the six years with the optimized and more profitable mix that would have been derived from approach 3. Comparing the programs and identifying the main divergences provides first evidence for systematic planning mistakes made by farmers.[7]

Table 4. Average Crop Proportions (in %) Empirically Realized by Farmers Compared to those Derived from the Superior Planning Approach 3

	Farm 1			**Farm 2**			**Farm 3**			**Farm 4**		
	Empirical	Optimized	Difference	Empirical	Optimized	Difference	Empirical	Optimized	Difference	Empirical	Optimized	Difference
Winter wheat	43.5	41.7	-1.8	22.1	25.9	3.8	42.4	40.8	-1.6	32.3	41.0	8.7
Spring wheat	0.0	0.9	0.9	0.0	0.0	0.0	0.0	0.6	0.6	–	–	–
Winter rye	22.3	39.0	16.6	16.2	38.3	22.1	19.3	30.7	11.4	24.4	31.7	7.3
Winter barley	13.6	0.0	-13.6	8.2	2.7	-5.6	15.8	8.6	-7.2	17.5	0.0	-17.5
Spring barley	1.2	0.0	-1.2	0.0	2.5	2.5	0.0	1.5	1.5	–	–	–
Winter canola	9.5	6.4	-3.1	15.6	8.8	-6.8	10.4	6.9	-3.5	9.4	13.2	3.7
Corn	0.0	0.0	0.0	15.1	0.2	-14.9	1.7	0.0	-1.7	–	–	–
Non-food canola	9.2	12.1	2.8	0.0	0.1	0.1	6.4	8.4	2.0	12.4	9.3	-3.1
Set-aside	0.8	0.1	-0.7	22.8	21.5	-1.3	3.9	2.4	-1.5	3.9	4.7	0.8

[7] We only comment on the benchmark comparison with approach 3. The production mix being very similar, identical conclusions are to be drawn from a comparison with approach 2.

The most noticeable result of the comparison is that, according to the superior planning approach 3, the proportion of (winter) rye should be increased significantly in all considered farms. Rye is very draught-resistant. From a crop science perspective it is thus especially well suited for the natural conditions of Brandenburg which are characterized by low and uncertain rainfalls as well as by poor and quickly draining soils. Searching for the most common and apparent change suggested by the formal planning approach 3, we may conclude that, besides farmer's 2 particular planning mistake regarding corn, all farmers should reduce their proportion of winter barley in favor of rye.

This result is an indication for systematic planning errors made by the farmers in the past. Evolutionary economics (cf. e.g. Nelson and Winter 1982) could be used to explain this finding: oftentimes, even important economic decisions are not supported by formal decision models. Rather, they are based on the decision-maker's experience gathered in the course of the past decades and on simple heuristics such as "never make any decision that differs very much from past ones" (cf. e.g. Gigerenzer and Selten 2001). In an environment where the relative competitiveness of different crops, e.g., changes quickly, decision-makers may thus not be quick enough to adapt to changed conditions. In other words: we might ask the question whether (boundedly rational) farmers making routine production program decisions learn too slowly. In the considered context it seems reasonable to speculate that farmers have not yet adapted their routines to account fully for two major changes of their relevant environment: on the one hand, the enormous progress in rye breeding over the last years which brought rye yields up to competitive levels, and, on the other hand, the increasingly precarious rain falls in Brandenburg, possibly caused by climatic change. Slow learning and adaptation, in turn, justifies the use of formal decision aids by farmers and extension services.

Summary and Conclusions

At first view, this paper seems to revive the discussion about the benefits of optimization models in applied agricultural program planning - a discussion that has been virtually closed in the past for the seemingly good reason that agricultural practitioners have found neither need nor want to use formal approaches in on-farm planning. Our exemplary analysis of four farms and six planning years, however, indicates that new grounds may be broken. The identified dimension and continuity of the efficiency gains that could have been achieved *if* systematic time series analysis and suitable stochastic optimization models had been used is quite astounding. In other words: using the hypothetical results resulting from the quasi ex-ante approach as a benchmark gives evidence that it is well worth the trouble to consistently use statistic information embodied in the farm-specific single gross margin time series.

The formal approach used in this study provides *practical* assistance for dealing with the problem of individual risk attitudes. It simply includes the variance of the total gross margin inherent to the production program chosen by the farmer as an additional restriction in the stochastic optimization model. Any practical decision support procedure which relies on this approach will thus require that farmers first specify their "own" production programs without the formal planning aid, thus providing an observable reflection of their risk attitude. Then, one can search for alternative programs which - with the same or even less variance - lead to superior or at least equal expected total gross margins. With regard to decision theory it must be recognized that the recommended alternative does *not* necessarily represent the solution that maximizes the farmer's utility. However, it generates extra value by providing practical decision support which - without the need to exactly specify the farmer's risk aversion or utility function - identifies *one* solution that increases the farmer's expected utility compared to his own routine-based decisions.

Our methodical comparison of different variants of statistical analysis (static distributions vs. stochastic processes) indicates that the extra value to be derived from formal optimization methods highly depends on the available data being *adequately* processed and used. Data may be time-dependent and thus exhibit e.g. a trend. This simple fact suffices to show that conventional approaches, which prima facie resort to the mean and variance of past values considered equal in weight, do not represent good forecasting models. Inserting too simplistic assumptions into formal planning models may well cause their performance to be inferior to that of routine planning based on rules of thumb. The lack of planning quality could thus be an explanation why the formal optimization approaches proposed in the past have not been accepted by farmers, and deservedly so.

While our analysis of four selected farms and six years provides first evidence for the potential of an adequate formal planning model to improve the efficiency of on-farm decision-making, its general value needs to be investigated through further research. The evident capacity to outperform farmers' routine decisions that was found in the case study warrants the effort. That is, we should test the model's robustness to provide superior results by applying it to a larger number of farms in different regions and with different farm sizes, production structures and operating figures. In this context the following extensions may prove valuable:

- As long as one is concerned with program planning on large farms, basically any crop rotation requirement can be translated into a respective (maximum or minimum) proportion of crops in any one year. This may be different on small farms where one needs to consider that fields, being of smaller but differing size, are not be further subdivided for different crops. Furthermore, soil quality may differ from one field to the other. Extending the model to include such field-specific information requires additional effort but could be implemented in principal.
- This paper solely addresses the partial planning problem "optimization of the production program“. The proposed planning approach extracts probabilistic information from the time series of *farm-specific* single gross margins. This is equivalent with considering both the limited resource supplies and the farmers' competencies regarding investment strategies and crop management as "givens". The planning model could be extended to include, e.g., the optimal specification of single production activities (with regard to the use of variable inputs and technologies etc.). After a change of management competence regarding, let's say, the factor intensities one needs to realize, however, that the farm-specific single gross margins observed in the past cannot be assumed any more to contain much useful information for the future. Instead one would need to resort to disaggregate values such yields, prices, input costs, etc.
- We included the total gross margin variance inherent to the farmer's observed program as a fixed restriction in the formal optimization model. Thus, we did not consider that farmers might be prepared, e.g., to accept some additional volatility if the expected increase of the total

gross margin covers their risk premium. That is, we cannot be sure to have found the utility maximizing production program. This does not impede the insights and clear-cut results of the analysis. In fact, the consequence is just that there may be even more room for improvement. One could investigate this by letting farmers choose from alternatives derived from a stepwise relaxation of the variance restriction. However, this means abandoning the model-endogenous recommendation of a single superior solution.

- In our case study, extending the time series model to include non-linear structures did not add much extra value compared to simple linear models. This can be seen as evidence that increasing planning efforts and further model sophistication do not pay due to decreasing marginal returns. It might nonetheless be worthwhile to search for models that perform still better. Such a search could include models which allow for process parameters that are variable over time. Explicit GARCH-models could, for instance, be used in the case of a time-variable variance (cf. Bollerslev 1986; Koekebakker and Lien 2004).

Decisions regarding the resources to be spent for planning are, like all economic choices, subject to efficiency considerations. Thus, additional efforts such as the introduction of formal and more sophisticated planning models need to be justified by additional benefits. In this context, one needs to know the economies of scale allowing for an efficient use of formal models in the first place. Furthermore, before plunging into any of the above-mentioned activities, it should be checked whether the informational gains justify the additional costs. The critical farm size allowing for sufficient economies of scale in planning depends on the costs (including learning costs) associated with the introduction of optimization models. These costs, in turn, depend on the intellectual capability and knowledge of farm managers and thus, amongst other things, on the quality of teaching. Better trained agricultural managers and consultants will need less time and effort to adopt more sophisticated approaches because they have less learning costs.

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