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# Identifying Risk-Efficient Crop Portfolios for Different Cropping Systems by Analyzing the Tradeoffs Between Arable Farming Profits and Profit Stability

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**Abstract:** As in agriculture uncertainties have increased due to extreme weather events and yield variations, a critical examination of crop rotation strategies is needed. This study analyses the relationship between risk and crop rotation planning, addressing the challenges posed by an increasing yield variability and related total contribution margin fluctuations. For the systems 'conventional farming', 'organic farming' and 'farming without pesticides, but with mineral fertilizer' time series data of crop yields, prices and variable costs are collected. The data is used for a Monte Carlo simulation that yields average contribution margins for the considered crops and their (co-)variances, which are needed to build a hypothetical model farm. Relying upon Quadratic Risk Programming, the expected total contribution margins are maximized for a set of fixed total contribution margin variances. Efficient frontiers are derived that show respective optimum combinations of the expected value of the total contribution margin and its standard deviation. Organic farming shows high average total contribution margins for optimized crop rotations, but also increased variance compared to other cropping systems. The inclusion of cereals in a crop rotation lowers the risk, whereas the inclusion of potatoes and sugar beet increases the risk within a crop portfolio across all systems. Optimizing and diversifying the crop portfolio for each cropping system is essential. An optimized farming system without pesticides, but with mineral fertilizer exhibits lower risk but also lower total contribution margin compared to other systems. This is due to a different crop portfolio but also to relatively low prices and yields.

**Keywords:** Risk Analysis, Monte Carlo Simulation, Quadratic Risk Programming, Farming Without Pesticides but with Mineral Fertilizer

## 1 Introduction

The choice of an appropriate crop rotation is a fundamental aspect when designing agricultural systems in a way to optimize yield, soil health, and overall sustainability (Lorenz et al., 2013; Sieling, Christen, 2015). The dynamic nature of agricultural markets and climatic uncertainties necessitates strategic planning of crop rotations to minimize risks while ensuring consistent productivity (Liu et al., 2016). Especially in recent times, there have been increasing uncertainties in the agricultural sector related to extreme weather events and crop yields (Söder et al., 2022). Yields but also yield variability have increased over time (Macholdt et al., 2021). Risk-averse farmers want to avoid high variability of income. Thus, they will implement crop portfolios that for given total contribution margins are characterized by a small variance of the latter.

Further, scientists emphasize the redesign of common cropping systems, e.g. conventional and organic agriculture, to enhance the sustainability and resilience of agricultural practices (Seufert et al., 2012). Consequently, some researchers have proposed the adoption of an arable farming system that bans the use of chemical synthetic plant protection products (i.e. “pesticides”), but allows the usage of mineral fertilizer (Jacquet et al., 2022; Zimmermann et al., 2021). However, the implementation of such an arable farming approach necessitates thorough research before putting it into practice. For example, Mack et al. (2023) recommends to include farmers` risk into profit maximization analysis. Hence, studies should consider not only the average expected profits but also the risk attitudes of farmers as well as aspects of changing production risk when choosing crop portfolios in different farming systems. This is all the more relevant as systems like arable farming without pesticides may be characterized by increased variance of the single crops’ contribution margins.

In this work, we first use a Monte Carlo simulation that simulates the contribution margins (CM) of eleven crops in three different cropping systems. Second, we use the Expected Value-Variance (EV) Criterion in a Quadratic Risk Programming (QRP) framework to estimate optimal crop portfolios for a given set of total contribution margin (TCM) variances. The objective is to offer insights into the design of robust and well adapted crop portfolios for respective cropping systems with relatively low variance of the TCM and, more generally, to derive efficient frontiers illustrating the corresponding trade-offs between average TCM and TCM variance. For the Monte Carlo simulation, time series data of producer prices, crop yields and variable costs are taken from different German statistics (see Section 2.1).

In the following, we analyze three farming system scenarios: (1, conventional) conventional arable farming restricted by policy measures that are mandatory; (2, organic) organic arable farming, where the use of mineral fertilizer and pesticides are forbidden; and (3, no pesticides) arable farming without pesticides, but with mineral fertilizer. For these systems, this research addresses the following questions:

**First**, to which extent does the variance of TCM of a crop portfolio increase as the number of crops in the rotation decreases? The corresponding hypothesis suggests that growing a greater variety of crops within the rotation considerably mitigates overall risk by decreasing yield variance as shown by Bowles et al. (2020), who analyzed long-term experiments in the USA and Canada and found that a diversified cropping system can reduce risk from yield loss.

**Second**, is the composition of the crop portfolio, for example, the share of grain legumes and non-cereal crops, changing with increasing production risk? This question arises from the assumption that risk-mitigating factors, like high crop diversity in the rotation or including certain crops with low yield variance, lead to relevant shifts in crop portfolio composition.

**Third**, what impact does the introduction of a relatively new crop, such as soy, have on the crop portfolio and resulting TCM in agricultural systems? Soy production is relatively new in Germany (Fogelberg, Recknagel, 2017). Additionally, Cellier et al. (2018) suggest that farmers might experience a learning curve when implementing new systems. Hence, this question acknowledges the potentially higher variance associated with new crops due to limited farming experience.

The remainder of this study is structured as follows: in **Section 2**, we reference relevant literature, formulate our research objectives and explain the material and methods used. In **Section 3**, the results of the simulation of the CMs and their temporal (co-)variances are presented, as well as the optimized crop rotations derived by QRP, with the respective TCMs and standard deviations. Additionally, a sensitivity analysis is presented. In **Section 4**, we discuss and summarize the answers to our research questions in light of existing agronomic knowledge.

# 2 Material and Methods

## 2.1 Methods

Following Hardaker et al. (2015), we employ QRP, which models a set of crop portfolios whose average TCMs and TCM standard deviations lie on the Expected Value-Variance (EV) efficient frontier. Assuming farmers with constant absolute risk aversion and a normally distributed TCM, Freund (1956) has shown that maximizing farmers' expected utility is equivalent to maximizing their certainty equivalent (CE). Then, every point on the efficient frontier corresponds to a CE maximization for a given absolute risk aversion. The farer to the left the respective point, the more risk-averse the respective utility maximizing farmer is.

The model farm and its restrictions are built with the focus on sound (not too narrow) crop rotations. Aspects that are important in practice, like labor hours and humus formation are considered in our model, but not included as limiting constraints, as they should not influence the crop portfolio. Only crop rotational constraints and mandatory policy measures are included as restrictive factors. The model farm could easily be adapted to the specific conditions of different arable farms.

Our model farm is located in Baden-Württemberg (BW), in the southwest of Germany. The average agricultural farm specialized in field crops in BW has 64.5 ha of arable land (FADN, 2024). To keep the model focused on CM variation, the model farm has 100 ha of arable land but no livestock. Note that for the analysis only optimized crop rotations without set-aside area are considered. For calculating the labor needs of the different crop portfolios, we assume a mechanization of 67 kilowatts, which is the base of the assumption for the working hours per hectare and crop. In BW, on the average a farm has 4.4 workers per 100 ha (Statistisches Landesamt Baden-Württemberg, 2022). In all models presented below, labor is abundantly available and will not be restrictive in order to illustrate the risk related impact on optimized crop rotations. The respective tables for all scenarios can be taken from the Appendix, as well as the assumptions for crop-specific humus formation or degradation (see Tables A1 to A5).

Crop rotation restrictions are important constraints for our model farm as they influence the possible combinations and shares of crops to be grown. In the 'Conventional' and 'No pesticides' scenario first, we consider crop rotation constraints that are due to phytosanitary reasons (see Table A6). Additionally, the mandatory policy rule Good agricultural and ecological condition of land (GAEC) 7 of the Common Agricultural Policy (CAP) is also taken into account in all scenarios (see Table A7)[1]. The crops we chose for our analysis of conventional and no pesticide farming are winter wheat (*Triticum aestivum L.*), rye[2] (*Secale cereale*), winter barley and spring barley (*Hordeum vulgare L.*), oats (*Avena sativa L.*), triticale *(×Triticosecale Wittmack*), potatoes (*Solanum tuberosum*), sugar beet (*Beta vulgaris L.*), winter rape (*Brassica napus*), silage corn (*Zea mays L.*) and soy (*Glycine max L.*).

For the 'Organic' scenario, we consider crop rotational constraints that result from phytosanitary recommendations in organic farming. These are stricter compared to conventional farming, as external pest control inputs such as pesticides are strictly regulated (Kolbe 2006). Although data could be gathered for the same crops as in the conventional farming scenarios, an exception was encountered concerning winter rape. To address this gap, we substituted winter rape, for which we had no yield data in organic farming with sunflower, for which we could

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1 GAEC are mandatory measures of the Common Agricultural Policy, which are basic requirements for farmers to receive any CAP area payments. This scheme requires crop rotation or cultivation of a catch crop or greening (Federal Ministry of Food and Agriculture, 2021).

2 The yield information for rye entails data from rye and winter cereal maslin. Rye is likely the predominant component, therefore, this crop is simply called 'rye'.

obtain yield information from organically cultivated sunflowers (*Helianthus annuus*). The corresponding maximum percentages of the different crops in the scenarios are summarized in Table 1. Kolbe (2008) recommends growing sugar beet and potatoes on a maximum of 20 to 25% of total arable land, respectively. In this work, this is further restricted to a maximum of 10%, respectively, because these crops are very susceptible to pests and require intensive pesticide use that is impossible in organic farming (Pawelzik and Möller, 2014; Stevanato et al., 2019). Hence, crop rotation is even more crucial for preventing pests (Pawelzik, Möller, 2014; Stevanato et al., 2019).

**Table 1. Crop rotation constraints for the farming scenarios 'Conventional', 'Organic' and 'No pesticides'**

| Scenario / Crop | Conventional % of arable land | Organic % of arable land | No pesticides % of arable land |
|---|---|---|---|
| Winter wheat | max. 33 | max. 30 | max. 33 |
| Rye | max. 50 | max. 30 | max. 50 |
| Winter barley | max. 33 | max. 25 | max. 33 |
| Spring barley | max. 33 | max. 30 | max. 33 |
| Oats | max. 25 | max. 16.7 | max. 25 |
| Triticale | max. 33 | max. 25 | max. 33 |
| Cereals | max. 75 | max. 66 | max. 75 |
| Potatoes | max. 25 | max. 10 | max. 25 |
| Sugar beet | max. 20 | max. 10 | max. 20 |
| Winter rape | max. 25 | - | max. 25 |
| Sunflower | - | max. 14.3 | - |
| Silage corn | max. 50 | max. 30 | max. 50 |
| Soy | max. 25 | max. 20 | max. 25 |

Source: modified after Kolbe (2008) and Federal Ministry of Food and Agriculture (2021)

Finally, utilizing the expected average contribution margins per crop ($\mu(CM_i)$), together with their corresponding covariances $Cov(CM_i, CM_k)$ and variances ($\sigma^2(CM_i)$) incorporated in the farm model, this study moves forward by employing QRP to derive the EV efficient frontier for the outlined farming systems and scenarios. The optimized crop portfolios are obtained by means of the Excel Solver. For the various farming scenarios, we identify different points on the efficient frontier, spanning from the risk-efficient crop rotation with the lowest risk, to the rotation with the highest possible risk. Maximization of expected total contribution margin given a fixed maximum variance $\sigma^2(TCM)^*$ can be expressed as follows (Hardaker et al., 2015):

$$\mu(TCM) = \sum_{i=1}^{I} \mu(CM_i)x_i \;\; max! \tag{1}$$

under the constraints

$$\sum_{i=1}^{I} x_i = AF \tag{2}$$

$$\sum_{i=1}^{I} a_{ji}x_i \;\le b_j \tag{3}$$

and

$$\sigma^2(TCM) = \sum_{i=1}^{I} x_i^2\, \sigma_i^2 + 2 \sum_{i=1}^{I}\sum_{i<k}^{I} x_i\, x_k cov(CM_i, CM_k) \quad \leq \quad \sigma^2(TCM)^* \tag{4}$$

where

$$CM_i = p_i y_i - vc_i \tag{5}$$

with

$\mu(TCM)$ = expected total contribution margin
$\mu(CM_i)$ = expected contribution margin per hectare of crop *i (i = 1, …, I)*
$CM_i$ = contribution margin of crop *i (i = 1, …, I)*
$p_i$ = price of crop *i (i = 1, …, I)*
$y_i$ = yield per hectare of crop *i (i = 1, …, I)*
$vc_i$ = variable cost per hectare of crop *i (i = 1, …, I)*
$x_i$ = cultivated hectares of crop *i (i = 1, …, I)*
*AF* = total available arable land of uniform quality of the model farm (in the presented model runs: *AF* = 100 ha)
$a_{ji}$ = crop rotation coefficient ($a_{ji}$ = 1 if crop *i* belongs to crop category *j*, 0 otherwise)
$b_j$ = maximum allowed area for crop category *j* (e.g., cereal crops) *(j = 1, …, J)*
$\sigma_i$ = contribution margin standard deviation of crop *i*
$cov(CM_i, CM_k)$ = contribution margin covariance for crops *i* and *k*
$\sigma^2(TCM)$ = variance of total contribution margin
$\sigma^2(TCM)^*$ = fixed maximum variance of total contribution margin.

The *J* crop rotation constraints (3) make sure that the optimized farm programs are in conformity with good agricultural practice (e.g., avoiding 100 % cereals in the crop rotation). The efficient frontier for a given cropping system is derived by applying the EV criterion and maximizing Equation (1) for different predefined levels of the variance of the total contribution margin ($\sigma^2(TCM)^*$ in Inequality (4)). It then shows optimized combinations of expected TCMs and TCM standard deviations, each combination standing for a specific level of risk aversion.

## 2.2 Data

The collection of time series data for crop yields ($y_i$), prices ($p_i$) and variable costs ($vc_i$) constitutes our initial step, as well as calculating standard deviations $\sigma(p_i)$, $\sigma(y_i)$ and Pearson correlation coefficients $\rho_{ik}$ (with $-1 \leq \rho_{ik} \leq 1$). This dataset is a fundamental requirement for the simulation of the crops' expected contribution margins ($\mu(CM_i)$) and their variances ($\sigma_i^2$). The former could also be calculated as

$$\mu(CM_i) = \mu(p_i y_i) - \mu(vc_i) = \mu(p_i)\mu(y_i) + \rho(y_i, p_i)\sigma(y_i)\sigma(p_i) - \mu(vc_i) \tag{6}$$

Our analysis covers major corps grown in BW. In 2022, cereals are grown on 469200 ha in BW, silage corn on 126300 ha, grain rape on 47300 ha, sugar beets on 19000 ha, potatoes on 5300 ha and soy on 8700 ha (Statistisches Landesamt Baden-Württemberg, 2022). We focus on primary crops within the crop portfolio and do not take into account catch crops, given their potential for relative unrestricted inclusion between growing seasons. The dataset for the respective crop yields[3], excluding soy, spans from 1999 to 2021 and originates from Main-

[3] The yield data also includes yields from organically grown crops. However as the organic share is only marginal it is supposed to have only little influence on the reported yield (Seitz, 2022).

Tauber-Kreis County, situated in the northern region of BW within the administrative region of Stuttgart (Statistische Ämter des Bundes und der Länder, 2023). This county is chosen as an example. Soy yields are unavailable for Main-Tauber-Kreis County due to its relatively recent introduction in German crop cultivation. Soy is not yet common and lacks comprehensive statistical documentation. Instead, soy yields for the business years 2000/01 to 2019/20 are sourced from the broader administrative region of Stuttgart[4].

Finally, to simulate time series of crop CMs, the inclusion of producer prices and variable costs is crucial. The producer prices for the years 1999 to 2021 for winter wheat, rye, winter barley, summer barley, oats, triticale, and rapeseed are obtained from Agrarmarkt Informations-Gesellschaft (AMI) (2010a, 2016, 2022) and Zentrale Markt- und Preisberichtstelle GmbH (ZMP) (2002, 2005). For soy, maize, sugar beets, and potatoes, the producer prices are sourced from KTBL[4]. In the absence of regional producer price statistics, we assume that producer prices remain uniform across Germany. The producer prices are exclusive of value-added tax.

The variable costs encompass expenses related to seeds, plant protection, fertilizer, variable mechanical costs, hail insurance, and, when relevant, post-harvest drying and cleaning procedures. Obtaining temporal variable cost data for BW over the past two decades proves to be a challenge. As a result, we resorted to utilizing time series data from Bavarian farms for nearly all analyzed crops from the years 2000 to 2021 provided by LfL[5]. There are less years available for maize, soy, sugar beet and triticale. The dataset of the variable costs involved value-added tax, which is assumed at 19 % and is extracted from the data.

In the context of our 'Organic' farming scenario, we collected yield data from the same crops as collected in the conventional scenarios. Unfortunately, the absence of accessible time series yield data for any county within BW necessitated our reliance on data from Bavarian organic farms once more, again provided by LfL. The yield data for all crops covers the years 2004 to 2021. Producer prices corresponding to organically grown crops in Germany, are exclusive of value-added tax, spanning the years 2004 to 2021 and were once more sourced from AMI (2010b, 2013, 2023) and LfL. As for the variable costs, there is no time series data available for organically grown crops, we had to resort to variable costs from the year 2021 and assume these costs are constant over the years. The variable costs are exclusive of value-added tax and sourced from LfL. The variable costs for organic arable farming include fertilizer costs according to nutrient removal. This means that the NPK (nitrogen, phosphorus, potassium) nutrient requirement is determined depending on the average harvested yield minus field losses and net nutrient costs are assumed. The NPK requirements and therefore, applied fertilizer can be taken from Table A4. The descriptive statistics of the variables yields, prices and variable costs from conventionally and organically grown crops can be found in Appendix Tables A8 and A9.

In the context of our farming scenario with mineral fertilizer, but without chemical synthetic plant protection products ('No pesticides'), the collection of time series data is unfeasible, as this innovative farming approach is not yet implemented in practice. Consequently, we extrapolated yield loss estimations utilizing insights from Röder et al. (2021) and from experimental trials conducted at the University of Hohenheim (https://nocsps.uni-hohenheim.de). In other words, we used time series yield data from our conventional farming scenarios and accounted for the presumed yield losses (see Table 2).

[4] Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (KTBL), https://www.ktbl.de/webanwendungen/standarddeckungsbeitraege

[5] Bayerische Landesanstalt für Landwirtschaft (LfL), https://www.lfl.bayern.de/index.php

**Table 2. Assumed yield losses for the scenario of arable farming without pesticides, but with mineral fertilizer**

| Crop | Assumed yield loss |
|---|---|
| Winter wheat | 30% |
| Rye | 25% |
| Winter barley | 40% |
| Spring barley | 20% |
| Oats | 20% |
| Triticale | 20% |
| Potatoes | 50% |
| Sugar beet | 40% |
| Winter rape | 45% |
| Silage corn | 15% |
| Soy | 50% |

Source: modified after Röder et al. (2021) and University of Hohenheim (https://nocsps.uni-hohenheim.de)

Producer prices for the scenario 'No pesticides' are sourced from the producer prices of our conventional farming scenarios. The variable costs associated with the 'No pesticides' scenarios are derived from both conventional and organic farming variable cost data as published by KTBL. It is assumed that variable costs are different from those in conventional farming due to the utilization of organic seeds, absence of chemical synthetic plant protection products and the inclusion of expenses for mechanical weed control. If applicable, costs associated with seasonal workers may also increase due to the implementation of more time-consuming mechanical pest control methods.

Lastly, time series data of yields, prices and costs of all scenarios are trend-adjusted. Linearly trend-adjusted estimated yield data and their corresponding standard deviations and correlations are calculated. The yield information is expressed in quintals[6] per hectare (dt/ha). All producer prices (in €/dt) and variable costs (in €/ha) have been adjusted for inflation up to the base year 2021 accounting for inflation rates in Germany from 2000 to 2020[7]. Finally, the trend adjustment of producer prices and variable costs is also done through linear regression analysis and corresponding standard deviations and correlations are calculated.

## 2.3 Empirical Implementation

Applying QRP to identify risk-efficient crop portfolios implies to have expected values and (co-)variances for all crops taken into consideration. In principle, the expected contribution margins could be obtained according to Equation (6), but for variances and covariances their direct calculation relying upon empirically derived yield and price variances turns out to be rather complicated if not even impossible[8]. For this reason, we make use of Monte Carlo simulations.

Deriving standard deviations ($\sigma_i$) and correlations ($\rho_{ik}$) from time series data of crop yields ($y_i$), producer prices ($p_i$) and variable costs ($vc_i$) as described in the previous section, a Monte Carlo simulation is performed to simulate expected contribution margins $\mu(CM_i)$ and their temporal (co-)variances. The Monte Carlo simulation is performed through Crystal Ball, a Microsoft

6 100 kg = 1 dt

7 Inflation rate in Germany according to Statistisches Bundesamt, 16. Januar, 2024. Inflationsrate in Deutschland von 1950 bis 2023. In: Statista, https://de.statista.com/statistik/daten/studie/4917/umfrage/inflationsrate-in-deutschland-seit-1948/, last accessed 25th of June 2024.

8 Only when disregarding covariances of prices ($cov(p_i, p_k)$) and yields ($cov(y_i, y_k)$), assuming a bivariate normal distribution of $p_i$ and $y_i$, the variances of the products $p_i\, y_i$ can be directly calculated once the expected values, variances and covariance of $p_i$ and $y_i$ are known (Bohrnstedt, Goldberger, 1969).

Excel add-in (Goldman, 2002). In 10000 runs $CM_i$s are computed according to Equation (5) for 10000 randomly drawn combinations of the input variables, assuming normal distribution and integrating non-negativity constraints so that prices, costs and yield cannot become negative.

The simulation accounts for correlations between the input variables. Hence, we use the Pearson correlation coefficients $\rho_{ik}$ (with $-1 \le \rho_{ik} \le 1$) between crops $\rho(y_i, y_k)$, prices $\rho(p_i, p_k)$ and between prices and crops $\rho(y_i, p_i)$ of the time series data (see Tables A10, A11 and A12)[9]. Considering corresponding correlations is of importance for achieving simulated output values that closely approximate real-world data.

It is not surprising to find statistically significant negative correlations between prices and yields of cereals such as winter wheat, rye, winter barley, spring barley, oats, and triticale. Furthermore, there is a statistically significant negative correlation between the price of winter rape and the yields of winter wheat, rye, and oats. But also winter rape price and winter rape yield have a statistically significant negative correlation. Interestingly, the prices of the considered cereals and winter rape have high positive significant correlations. In contrast, certain yields of crops such as winter barley, silage corn, and soy show either no significant correlations or only few statistically significant correlations with the yields and prices of other crops. Historical time-series data concerning yield and producer prices are available for all observed conventionally grown crops except soy. Information about organically cultivated crops is, however, limited. This is also evident in the reduced number of statistically significant correlations observed in our ‘Organic’ scenario. Notably, in the ‘Organic’ scenario, there are no statistically significant relationships between cereal prices and yields except for rye. Similar to the ‘Conventional’ scenario, cereal prices have significant, relatively high positive correlations.

For our third scenario, farming without pesticides, but with mineral fertilizer, again assumptions must be made due to data limitations. In the absence of hypotheses or empirical evidence of correlation, the same correlations as in our ‘Conventional’ scenario were used for the simulation process of ‘No pesticides’. We take conventional prices and yields (accounting for yield losses as given in Table 2) with time series data from conventionally grown crops.

# 3 Results

In this section, we illustrate the expected CMs and their (co-)variances derived from the Monte Carlo simulations and compare the (co-)variances of the different scenarios and show the results obtained by QRP when applying the EV criterion for the scenarios of conventional farming, organic farming, and farming without pesticides, but with mineral fertilizer. Lastly, we present the results from three extended scenario analyses.

## 3.1 Simulated Average Contribution Margins and Their (Co-)Variances

Table 3 illustrates the simulated average CMs for the crops considered in the QRP model. Remarkably, in the ‘Organic’ scenario, all crops except silage corn and triticale exhibit high average CMs. Particularly noteworthy are the substantial expected CMs observed for sugar beet, potatoes, and soy in the ‘Organic’ scenario. Conversely, the scenario ‘No pesticides’ results in negative CMs for these three crops. Additionally, this scenario shows lower CMs for all crops compared to the other two scenarios.

[9] Note that only statistically significant correlations are submitted to Crystal Ball. All others are set to zero. In case of inconsistent correlations, Crystal Ball corrects correlations marginally.

**Table 3. Simulated average contribution margins ($\mu(CM)$) in Euro/hectare (€/ha) for all scenarios**

| Contribution margins (€/ha) | Winter wheat | Rye | Winter barley | Spring barley | Oats | Triti-cale | Pota-toes | Sugar beet | Winter rape | Sun-flower | Silage corn | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Conventional | 535 | 399 | 271 | 377 | 441 | 668 | 1262 | 830 | 739 | | 463 | 437 |
| Organic | 839 | 432 | 641 | 881 | 1019 | 580 | 10914 | 10436 | | 827 | 249 | 1960 |
| No pesticides | 272 | 242 | 66 | 288 | 291 | 550 | -2414 | -1604 | 376 | | 124 | -266 |

Note: ‘Conventional’ = conventional farming scenario; ‘Organic’ = organic agriculture;
‘No pesticides’ = Farming without pesticides, but with mineral fertilizer
Source: own calculations

The simulated CM variances and covariances utilized in the QRP for the respective scenarios can be taken from Appendix Tables A13 through A15. The latter are crucial due to their effect on the total variance of the optimized crop portfolio (see Inequality (4)). It can be seen from the tables that nearly all the (co-)variances associated with the conventional farming scenarios are lower, compared to the (co-)variances observed in the organic farming scenario. Additionally, the ‘Conventional’ farming scenario has several negative covariances, mainly for soy, while the organic farming scenario shows only few negative covariances and none for soy. Soy has a considerably higher variance than most cereal crops in the scenarios. Another remarkable figure is the potato CM variance, which is considerably higher than all other crop CM variances. The (co-)variances of the CMs for the scenario ‘No pesticides’ are notably lower. Moreover, again there are some negative covariances, especially for soy. The low (co-)variances are probably due to the limited price, yield and variable cost data that are available for the scenario. In all scenarios, the covariance between rye and silage corn is particularly low. This could be due to several factors. One possible explanation is the divergence in sowing, germination, and harvesting dates for these two crops. Another assumption is that distinct market influences are at play. For instance, the demand for rye and silage corn may fluctuate at different times, causing prices and yields to respond independently of each other.

## 3.2 Optimization for the Conventional Farming Scenario

Evidently, in this scenario a stepwise reduced variance $\sigma^2(TCM)$ (see inequality (4)), indicative of lower risk, corresponds to a diminished TCM. In the extreme case, the crop portfolio encompasses eight crops (see Table 4). Conversely, a higher given standard deviation limit leads to an increased TCM but entails a reduced crop count, with finally only four crops included. Additionally, the integration of soy and silage corn reduces the variance. As risk increases (as indicated by a higher standard deviation *σ(TCM)*), the cultivation strategy shifts towards crops characterized by both high per hectare CMs and variances.

**Table 4. Optimized crop portfolio of the farming scenario 'Conventional'**

| Hectares of crops grown on the arable land of the 'conventional' model farm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triti-cale | Pota-toes | Sugar beet | Winter rape | Silage corn | Soy | Standard deviation σ(TCM) | Total contribution margin (TCM) in Euro |
| 0 | 4 | 0 | 11 | 1 | 18 | 0 | 12 | 25 | 13 | 17 | 17321 | 59595 |
| 4 | 0 | 0 | 0 | 0 | 27 | 0 | 15 | 25 | 11 | 18 | 20000 | 64100 |
| 4 | 0 | 0 | 0 | 0 | 31 | 0 | 20 | 25 | 4 | 15 | 22361 | 67058 |
| 7 | 0 | 0 | 0 | 0 | 33 | 2 | 20 | 25 | 1 | 12 | 24495 | 69082 |
| 9 | 0 | 0 | 0 | 0 | 33 | 4 | 20 | 25 | 0 | 9 | 26458 | 70597 |
| 11 | 0 | 0 | 0 | 0 | 33 | 5 | 20 | 25 | 0 | 6 | 28284 | 71848 |
| 12 | 0 | 0 | 0 | 0 | 33 | 6 | 20 | 25 | 0 | 4 | 30000 | 72937 |
| 13 | 0 | 0 | 0 | 0 | 33 | 7 | 20 | 25 | 0 | 2 | 31623 | 73914 |
| 6 | 0 | 0 | 0 | 0 | 33 | 16 | 20 | 25 | 0 | 0 | 44721 | 80693 |
| 0 | 0 | 0 | 0 | 0 | 32 | 23 | 20 | 25 | 0 | 0 | 54772 | 85251 |
| 0 | 0 | 0 | 0 | 0 | 30 | 25 | 20 | 25 | 0 | 0 | 58332 | 86669 |

Source: own calculations

## 3.3 Optimization for the Organic Farming Scenario

In this scenario, the farmer grows at least six main corps (see Table 5). With an increasing TCM standard deviation, there comes a point where the farmer will integrate seven crops into their crop portfolio, although spring barley then makes only a small share of 3%. In all, the inclusion of winter wheat and sunflower into the crop rotation decreases the TCM standard deviation. As the standard deviation is allowed to increase, there is a shift in the crop selection: winter wheat and sunflower are successively replaced by spring barley. Also note the amount of the expected TCM, which is remarkably high. See Figure 1 for an illustration of the efficient frontiers of the conventional and organic farming scenario.

**Table 5. Optimized crop portfolio of the 'Organic' farming scenario**

| Hectares of crops grown on the arable land of the 'organic' model farm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triti-cale | Pota-toes | Sugar beet | Sun-flower | Silage corn | Soy | Standard deviation σ(TCM) | Total contribution margin (TCM) in Euro |
| 30 | 0 | 0 | 0 | 17 | 0 | 9 | 10 | 14 | 0 | 20 | 40000 | 296153 |
| 30 | 0 | 0 | 0 | 16 | 0 | 10 | 10 | 14 | 0 | 20 | 41231 | 302248 |
| 30 | 0 | 0 | 3 | 17 | 0 | 10 | 10 | 10 | 0 | 20 | 42426 | 306084 |
| 30 | 0 | 0 | 11 | 17 | 0 | 10 | 10 | 3 | 0 | 20 | 43589 | 306489 |
| 26 | 0 | 0 | 17 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 44721 | 306787 |
| 20 | 0 | 0 | 23 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 45826 | 307025 |
| 13 | 0 | 0 | 30 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 47333 | 307323 |

Source: own calculations

## 3.4 Optimization for the Farming Scenario with Mineral Fertilizer, but Without Pesticides

Table 6 illustrates that, with a lower TCM standard deviation, the portfolio consists of five primary crops. In this case, silage corn stands for 6% of the crop portfolio. Compared to that, for a high given standard deviation, the crop portfolio consists of only four crops. As the standard deviation *σ(TCM)* increases, the share of silage corn and spring barley in the crop portfolio decreases, being mainly substituted by oats and triticale. Figure 2 shows the efficient frontier of the farming scenario with mineral fertilizer, but without pesticides.

**Table 6. Optimized crop portfolio of the scenario 'No pesticides'**

| Hectares of crops grown on the arable land of the 'No pesticides' model farm | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Pota-toes | Sugar beet | Winter rape | Silage corn | Soy | Standard deviation σ(TCM) | Total contribution margin (TCM) in Euro |
| 0 | 0 | 0 | 33 | 11 | 25 | 0 | 0 | 25 | 6 | 0 | 14142 | 36493 |
| 0 | 0 | 0 | 33 | 9 | 27 | 0 | 0 | 25 | 6 | 0 | 14491 | 37229 |
| 0 | 1 | 0 | 33 | 7 | 30 | 0 | 0 | 25 | 5 | 0 | 14832 | 37923 |
| 0 | 1 | 0 | 33 | 6 | 32 | 0 | 0 | 25 | 4 | 0 | 15166 | 38579 |
| 0 | 0 | 0 | 33 | 6 | 33 | 0 | 0 | 25 | 3 | 0 | 15492 | 39204 |
| 0 | 0 | 0 | 31 | 11 | 33 | 0 | 0 | 25 | 0 | 0 | 15811 | 39654 |
| 0 | 0 | 0 | 23 | 19 | 33 | 0 | 0 | 25 | 0 | 0 | 16125 | 39679 |
| 0 | 0 | 0 | 17 | 25 | 33 | 0 | 0 | 25 | 0 | 0 | 16432 | 39699 |
| 0 | 0 | 0 | 17 | 25 | 33 | 0 | 0 | 25 | 0 | 0 | 16442 | 39700 |

Note: 'No pesticides' = farming without pesticides, but with mineral fertilizer
Source: own calculations

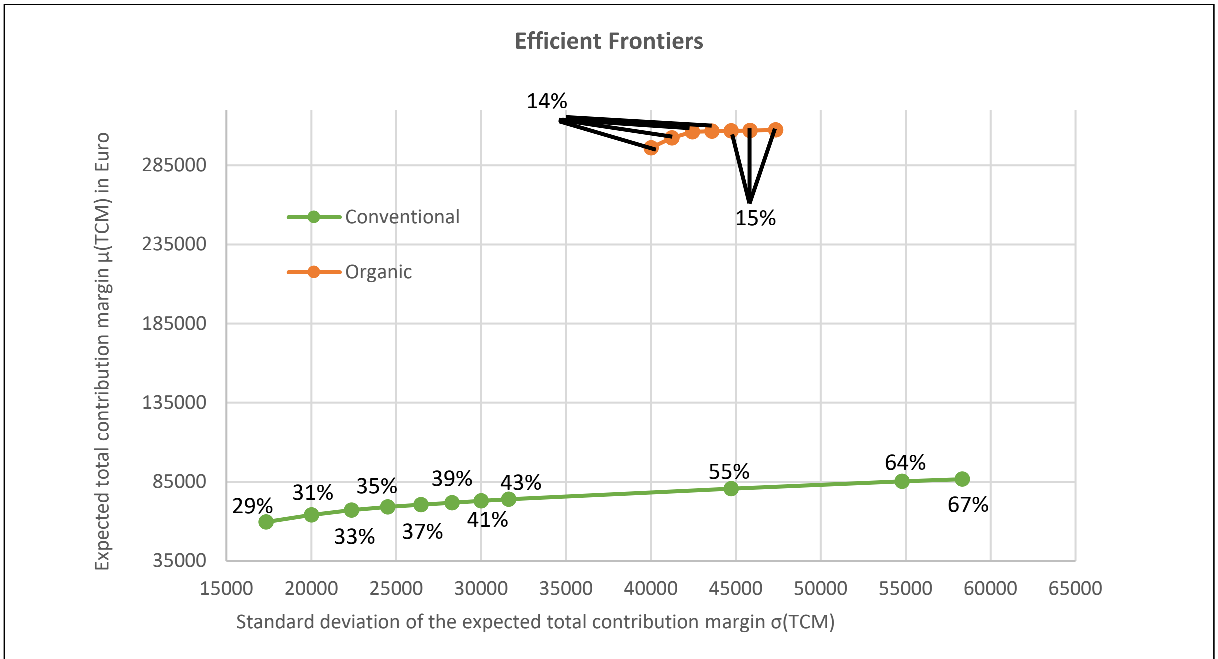


**Figure 1. Efficient frontiers for the 'Conventional' and the 'Organic' scenarios with coefficients of variation for different points on the frontier**

Note: Coefficient of variation = σ(TCM)/μ(TCM) 'Conventional' = conventional farming scenario with basic common agriculture policy restrictions; 'Organic' = organic agriculture
Source: own calculations

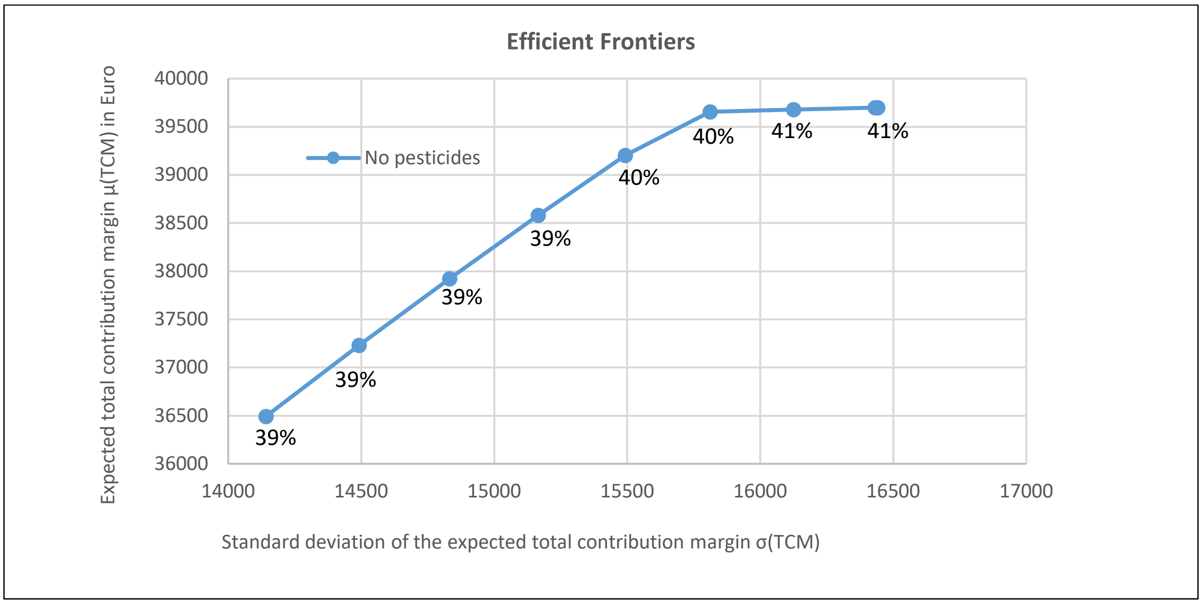


**Figure 2. Efficient frontier for the 'No pesticides' scenario with coefficients of variation for different points on the frontier**

Note: Coefficient of variation = σ(TCM)/μ(TCM); 'No pesticides' = farming with mineral fertilizer, but without pesticides
Source: own calculations

## 3.5 Sensitivity Analysis

The sensitivity analysis evaluates the consequences of increased soy CM variances. Organic farming necessitates a grain legume due to phytosanitary reasons. As soy is the sole grain legume in our model, its cultivation becomes obligatory and is limited to a maximum of 20 hectares. For the 'No pesticides' and for the 'Conventional' farming scenario a corresponding restriction is inserted. Specifically, in these two cases soy must be cultivated on at least 10 hectares. In the reference scenario 'Conventional' the soy CM variance is 145275. In the reference scenario 'Organic' it increases to 235746, and in the scenario labeled 'No pesticides', the soy variance reaches 35680. For this analysis focusing on 'increased soy variance', we deliberately raise the CM variance values for all three aforementioned scenarios to 500000. This ad hoc adjustment is based on the assumption that soy cultivation is relatively new in Germany (Fogelberg, Recknagel, 2017). As a result, farmers lack experience in its cultivation. This inexperience is likely to lead at least initially to relatively high yield deviations.

The resulting crop portfolios and respective coefficients of variations can be seen in the Appendix (see Tables A16 to A18). Figure 3 illustrates the resulting TCMs and TCM standard deviations. A noteworthy observation is that the base scenario and the result of the analysis for the 'organic' system show only marginal differences. In the conventional scenario with increased soy variances, it can be seen that especially at the beginning of the possibility range the TCM is lower when the risk is approximately the same as in the base scenario. The increased soy CM variance has a pronounced impact in the 'No pesticides' scenario. It offers a lower range of possible options compared to its base scenario with lower TCM. This is largely due to the unfavorable CM of soy in this type of farming which is -266 €/ha. Additionally, it experiences the highest increase of the soy variance in relation to the other two scenarios.

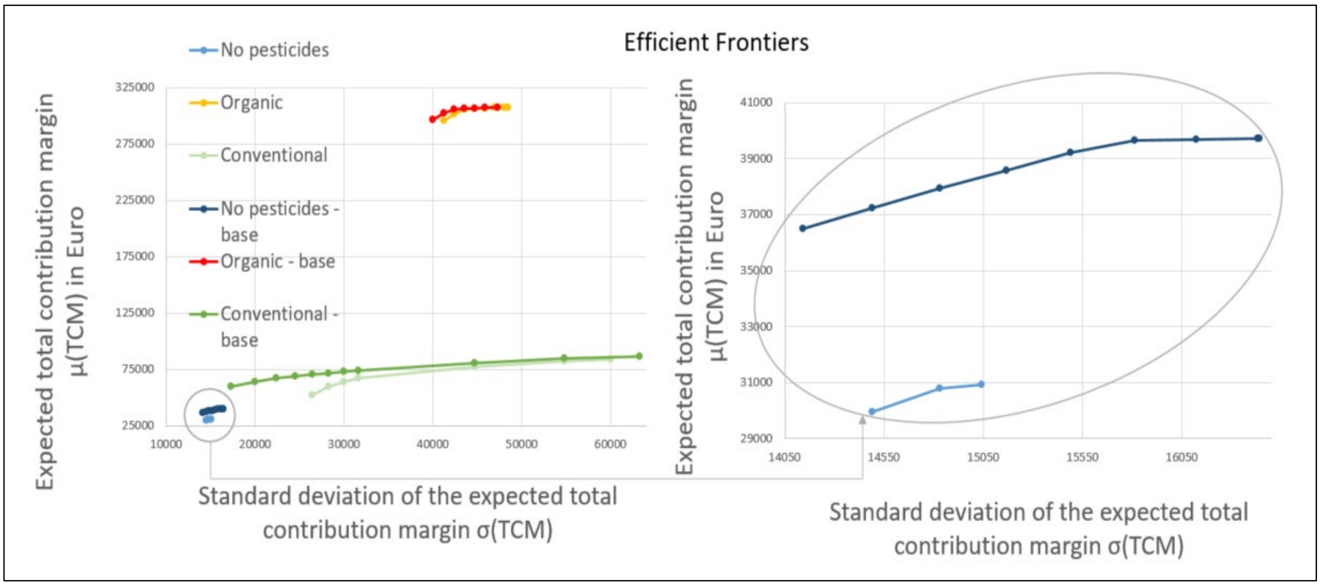


**Figure 3. Efficient frontiers for the analyses 'Increased soy variance'**

Note: 'Conventional - base' = 'Conventional' farming scenario; 'Conventional' = 'Conventional' farming scenario with increased soy contribution margin variance and at least 10 ha of soy in the crop portfolio; 'Organic – base' = organic agriculture; 'Organic' = organic agriculture with increased soy contribution margin variance and at least 20 ha of soy in the crop portfolio; 'No pesticides – base' = farming without pesticides, but with mineral fertilizer; 'No pesticides' = farming without pesticides, but with mineral fertilizer with increased soy contribution margin variance and at least 10 ha of soy in the crop portfolio
Source: own calculations

## 4 Discussion and Conclusions

For realistic empirically based price, yield and cost data, we have demonstrated that a reduction in the number of crops within a rotation leads to an increase in the variance of TCM of a crop portfolio. This pattern is observable across all cropping systems, with a particularly pronounced effect in our 'Conventional' scenario, where the number of crops in the rotation is halved for an increased TCM variance. In contrast, the relationship is not as evident in the other scenarios, mainly due to the constraints that enforce a more diverse crop rotation for phytosanitary reasons. Notably, in conventional farming, these phytosanitary restrictions are less stringent, as pests can be controlled through the application of pesticides.

### 4.1 Number of Crops in the Rotation Influencing the Total Contribution Margin

Our **first** research question investigates to which extent the variance of the TCM of a crop portfolio increases as the number of crops in the rotation decreases. This question has been answered by the results shown in Tables 4 through 6. It can be seen that the 'Organic' scenario and the 'No pesticide' scenario both do not have a large increase of the TCM standard deviation (see Figures 1 and 2, where we also give the corresponding coefficients of variation). In contrast, the 'Conventional' scenario displays the most pronounced increase in both standard deviation and expected TCM. This is due to fewer restrictions and thus a greater range of possibilities.

Despite higher variances of the single organically grown crops the TCM variance does not increase that much as due to the crop rotation restrictions it is not possible to grow crops like potatoes to a larger extent. Seufert (2019) provided for evidence supporting the hypothesis that yields in organic farming are more unstable over time compared to yields in conventional farming. For organically grown soy the higher CM variance results from lower price stability.

The TCM is notably high in the organic farming scenario, primarily due to recent increases in producer prices and high average yields of potato and sugar beet. In our analysis, we used the prices for table potatoes, which tend to be higher than those for feeding potatoes. This choice was made to reflect the market dynamics of organic farming, where table potatoes are typically considered a higher-value product due to their suitability for direct consumer consumption. Furthermore, the costs associated with organic table potato production have been relatively low in recent years, largely due to favorable weather conditions, particularly dry weather, which has reduced the prevalence of fungal diseases. This reduction in disease pressure has contributed to lower production costs for organic potatoes, as fewer resources are required for pest and disease management. However, it is crucial to note that these favorable weather conditions are not guaranteed to persist. Changes in weather patterns, particularly in the context of climate change, could significantly alter the cost structure of organic potato production and also affect its CM variance.

However, the increased TCM must be seen in context with the increased labor hours in this scenario (see Tables A19 to A21 in the Appendix). The ‘Organic’ scenario demands the highest total working hours (approximately 3000 hours per year). This has to be seen in relation to the relatively high TCM in organic farming. Conversely, the ‘Conventional’ scenarios yield lower TCMs but also exhibit lower working hour requirements, ranging between 1000 to 1800 hours only. On average, labor demand in organic farming is about twice as high as in the conventional system. In contrast, the ‘No pesticides’ scenario has notably lower total working hours of about merely 800 hours. Notice that in our scenarios, labor is assumed to be freely available at farm level. If in the organic model farm the amount of labor exceeding the labor needs of the conventional farm was to be paid to employees at a wage rate of €20 per hour this would entail up to 40000 Euros of additional cost resulting in a corresponding downward shift of the organic efficient frontiers in Figures 1 and 3. Clearly, the ‘No pesticides’ scenario cannot compete economically as its TCM is much smaller. Risk considerations are unlikely to outweigh this disadvantage when switching from one system to the other. Thus, a price premium is necessary. This conclusion is supported by Möhring, Finger (2022), who also assumed that a price-mark up is necessary for compensation. In this context, previous studies have demonstrated a consumer willingness to pay for organic produce and for products produced without pesticides (Bazoche et al., 2012; Nitzko et al., 2024; Wendt, Weinrich, 2023).

As expected, organic farming proves to be not only economically competitive but also shows better humus values than conventional farming. It is known that organic farming contributes to better soil health (Mäder et al., 2002). However, a similar effect can only be assumed for the new farming system without pesticides, but with mineral fertilizer due to a lack of long term experiments. The optimized crop portfolio in the ‘No pesticides’ scenario also yields positive outcomes for the humus balance (see Tables A1 and A21 in the Appendix).

## 4.2 Changing Composition of the Crop Portfolio as Risk Increases

The optimized crop portfolios of the various farming scenarios consist of different crops. For instance, in the conventional farming scenario, a low-risk crop portfolio comprises a higher proportion of cereals (rye, spring barley, oats, triticale) and winter rape, silage corn and soy, while the optimized high-risk crop portfolio includes only one cereal (triticale), excludes silage corn and soy, but adds potatoes. In the low-risk organic optimization, for instance, sunflower and winter wheat is included, whereas in the high-risk variant, winter wheat is reduced, spring barley is added, and sunflower is excluded. Note that growing a legume (soy) is compulsory in organic farming. In the ‘No pesticides’ scenario, the low-risk variant includes three cereals (spring barley, oats, triticale), but also winter rape and silage corn, whereas the high-risk optimization results in the same crops but silage corn.

Consequently, we can address our **second** research question: is there a change in the composition of the crop portfolio as production risk increases? In low-risk scenarios, silage corn is often included and a higher proportion of cereal crops is cultivated compared to high-risk scenarios. As the allowed level of risk increases, there is an increase in the share of potatoes and sugar beets, with one notable exception. In the scenario without pesticides, but with mineral fertilizers, neither potatoes nor sugar beets are cultivated in any of the QRP optimizations. Winter rape is consistently a part of the crop portfolio in all scenarios, but in organic farming, where the winter rape option had to be replaced by the possibility to grow sun flower due to data availability reasons.

These results can be explained by the differing variances of the crops' CMs. For instance, potato and sugar beet have notably high CM variances in all scenarios, whereas wheat and rye show lower variances. Our findings are supported by analyses of yield stability in the literature, which also rank winter wheat as having the highest stability (i.e. the lowest variance), followed by rye, sugar beets, and potatoes as the least stable (Ahrends et al., 2021; Reckling et al., 2018). In the scenario without pesticides, but with mineral fertilizer, potatoes are not cultivated due to a negative average CM. Potatoes are particularly vulnerable to fungal diseases. In a year characterized by increased precipitation and warm temperatures, the application of fungicides would become imperative (Dachbrodt-Saaydeh et al., 2021). Consequently, it is rational to abstain from growing potatoes in this farming system. Conversely, in a relatively high-risk organic farming scenario, the cultivation of potatoes is profitable despite the absence of fungicide applications and a high CM variance, mainly because of the increased producer prices and low costs in recent years.

In general, it should be noted that crop diversification plays a crucial role in reducing pesticide dependency. This is caused by the inclusion of crops with low pesticide requirements into the rotation (known as the 'dilution effect') and by the cultivation of crops that actively mitigate the appearance of pests, weeds, and diseases, referred to as the 'regulation effect' (Guinet et al., 2023). Notice that in our model analyses we merely consider effects on the variance due to the composition of the crop portfolio under the assumption of constant (co-)variances of the single crops, no matter how the portfolio is composed. Variance effects that result from different combinations of the crops cannot be simulated in our analysis but are likely to be relevant in practice. For example, Reckling et al. (2016) show, that introducing grain legumes into a rotation can have positive phytosanitary effects. However, in their analysis, CMs are lower in cropping systems with grain legumes.

## 4.3 Impact of a New Crop on the Total Contribution Margin and Crop Portfolio

Typically, yields of grain legumes are as reliable as cereal yields (Reckling et al., 2018). Soy is a grain legume but it is a relatively new crop for German farmers, and as a result, lower stability may be anticipated due to a lack of experience. The **third** research question treats the impact of the introduction of such a new crop on the TCM and the crop portfolio in agricultural systems. To answer this question, we conduct an analysis, where the CM variance of soy is increased and soy becomes a mandatory part of the crop rotation.

While the CM variance of soy in the 'Organic' scenario nearly doubles and in the 'Conventional' scenario more than triples, there is nearly no impact on the crop portfolio. The number of data points on the EV frontier remain nearly unchanged, and the TCMs for the optimized crop portfolios remain close to the base scenarios. In the 'No pesticides' scenario, the assumed CM variance of soy is approximately 14 times higher than that in the base scenario. Further, there is a decrease of the TCM for the optimized crop portfolio compared to its base scenario because of the negative CM of soy in this scenario (in contrast to the 'Conventional' and the 'Organic' scenarios that show positive soy CMs). Hence, a price premium is necessary to cover costs and make the crop profitable in the system without pesticides, but with mineral fertilizer. Other studies also found, that soy is competitive in organic and conventional agriculture in Germany (Böttcher, Zimmer, 2021; Fogelberg, Recknagel, 2017).

## 4.4 Caveats

It is crucial to acknowledge the caveats of this analysis: the costs play an essential role when undertaking comparisons between farming systems, evaluating their respective expected TCMs, and assessing associated risks. Pimentel et al. (2005), for instance, provide detailed explanations of various input costs for conventional and organic agriculture. For an innovative farming system such as farming without pesticides, but with mineral fertilizer, input costs have to be presumed. We assume that variable costs of such a farming system differ from those in conventional farming due to the utilization of organic seeds, absence of chemical synthetic plant protection products and expenses for mechanical weed control including higher work load for seasonal workers. However, there is evidence that variable costs are further reduced by a decreased level of applied mineral fertilizer, though there are no findings, by how much mineral fertilizer should be reduced (Pergner, Lippert, 2023).

Further, data limitations for time series data of producer prices and yields for the farming system without pesticides, but with mineral fertilizer and for organic farming yield data in BW have to be acknowledged. Ideally, this analysis would build on data from three different farms that are located in the same area and each adopted one of the analyzed farming systems for the last 20 years. A corresponding optimization with farm-level data of a conventional farm is done in Mußhoff, Hirschauer (2007a) and Mußhoff, Hirschauer (2007b). Another approach would be to analyze time series yield data from experiments for yield stability (Pergner et al., 2024; Schmidt et al. 2023). However, for new farming systems data from farms and from experiments are not available. Consequently, in this case, we had to resort to scenario analyses based on plausible assumptions derived from observations for existing farming systems and our scenario analyses do not claim for representativeness. Additionally, we assumed normal distributions of prices, costs and yields. While this approximation simplifies modeling and is commonly used in similar studies, we acknowledge that it may not fully capture the complexities of agricultural risk, especially when (in the future) extreme weather events may occur more frequently because of ongoing climatic change. Despite the necessary approximation of price and yield distributions (unavoidably based on past observations), we are confident that we developed an approach that yields informative and conclusive results.

In addition to risk and risk attitude, other important factors affect farmers' decisions to adopt or switch to alternative crop portfolios or cropping systems, such as the lock-in effect, perceived work load, investment and transaction costs when switching to another farming system, the availability of workers, and administrative burden that may come along with new techniques and certifications (Delbridge et al., 2017; Kuminoff, Wossink, 2010; Pergner, Lippert, 2023). Moreover, a farmer's entrepreneurial identity plays an important role in determining crop selection, with key factors apart from their willingness to take risks, like openness to innovation, confidence in influencing the farm's success, along with their age, farm size, and level of education (Suvanto et al., 2020). In this context, it should also be noted that income can play a significant role in shaping an individual's risk-taking behavior. Generally, higher income levels can provide a sense of financial security, allowing individuals to be more comfortable with taking risks. Farmers with higher incomes may have more disposable income, which can act as a buffer against potential losses. On the contrary, farmers with lower incomes are likely to be more risk-averse, given their limited financial margin for potential setbacks. Hence, wealthier farmers may feel more financially secure, enabling them to take calculated risks in experimenting with new crops, technologies, or farming practices. This can lead to increased experimentation and adaptation to new and more efficient farming methods.

Chavas, Di Falco (2012) demonstrate that economies of scope resulting from complementarity effects are achievable. Thus, reducing risk and at the same time achieving economies of scope through crop diversity seems feasible. However, this work focuses on risk related to yield stability as a primary distinctive feature of different cropping systems. It should be acknowledged that beyond crop diversification numerous other options for farm diversification and risk mitigation are available. Furthermore, the CMs and the (co-)variances assumed for the model optimizations reflect the current state and remain constant for our analyses. However, with crop rotation changes, growing expertise in new cropping systems, and the adoption of innovative technologies, there is the potential for future improvements in yields, reductions in costs and/or CM variances. This would have an impact on expected TCM and could also result in the decline of its standard deviation.

In conclusion, this study serves as a framework for informed agricultural planning by highlighting the role of crop rotation optimization in managing risk. The assessment of expected CMs and their (co-)variances, and resulting (optimized) crop portfolios provides comprehensive insights for evaluating the multifaceted dimensions of risk in different farming systems. By considering both, overall financial performance and risk exposure, farmers can make more informed decisions that align with their economic objectives and individual risk attitudes. It becomes clear that crop portfolios should be optimized individually and are to be analyzed separately for different farming systems. In the future, the approach illustrated by our study should also be carried out with time series data from given farms. This would allow for analyzing the cropping systems at real farm level, comparing their achievable TCMs und related temporal (co-)variances and, finally, contribute to identifying site- and farmer-specifically well adapted resilient cropping systems.

## Data Availability Statement

The data that support the findings of this study can be made available by the corresponding author Isabell Pergner upon request.

## Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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# Appendix

## Assumptions for the Farm Model

**Table A1. Evaluation of humus balances**

| Humus equivalent (heq) /hectare/year for conventional farm | Humus equivalent (heq) /hectare/year for organic farm | Category |
|---|---|---|
| <-200 | <-200 | A very low |
| -200 to -76 | -200 to -1 | B low |
| -75 to 100 | 0 to 300 | C balanced |
| 101 to 300 | 101 to 500 | D high |
| > 300 | > 500 | E very high |

Source: Verband Deutscher Landwirtschaftlicher Untersuchungs- und Forschungsanstalten (2014)

**Table A2. Assumed factor demands for conventionally grown crops**

| Crops | Working hours per hectare | Humus formation/degradation Humus equivalent/hectare/year |
|---|---|---|
| Winter wheat | 10.96 | 100,00 |
| Rye and winter meslin | 9.73 | 100,00 |
| Winter barley | 10.48 | 100.00 |
| Spring barley | 9.53 | 100.00 |
| Oats | 9.47 | 100.00 |
| Triticale | 9.85 | 100.00 |
| Potatoes | 42.11 | -760.00 |
| Sugar beet | 11.15 | -760.00 |
| Winter rape | 9.79 | 100.00 |
| Silage corn | 11.62 | -560.00 |
| Soy | 8.42 | 600.00 |

Source: Verband Deutscher Landwirtschaftlicher Untersuchungs- und Forschungsanstalten (2014) and Kuratorium für Technik und Bauwesen in der Landwirtschaft e. V. (2023)

**Table A3. Assumed factor demands for organically grown crops**

| Factor demands | Working hours per hectare | Humus formation/degradation Humus equivalent/hectare/year |
|---|---|---|
| Winter wheat | 9.59 | 100.00 |
| Rye and winter meslin | 9.26 | 100.00 |
| Winter barley | 9.38 | 100.00 |
| Spring barley | 12.63 | 100.00 |
| Oats | 9.91 | 100.00 |
| Triticale | 9.66 | 100.00 |
| Potatoes | 58.62 | -360.00 |
| Sugar beet | 177.14 | -360.00 |
| Sunflower | 12.34 | 100.00 |
| Silage corn | 11.62 | -560.00 |
| Soy | 15.94 | 600.00 |

Source: Verband Deutscher Landwirtschaftlicher Untersuchungs- und Forschungsanstalten (2014) and Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (2023)

**Table A4. The nutrient requirement per crop in the organic farming scenario depending on the average yield**

| **Nutrient requirement and applied fertilizer (kg/ha)** | **Nitrogen** N | **Phosphate** P2O5 | **Potassium** K2O |
|---|---|---|---|
| Winter wheat | 87 | 33 | 23 |
| Rye and winter meslin | 50 | 27 | 20 |
| Winter barley | 67 | 33 | 24 |
| Spring barley | 51 | 30 | 22 |
| Oats | 56 | 30 | 22 |
| Triticale | 67 | 33 | 24 |
| Potatoes | 83 | 33 | 142 |
| Sugar beet | 94 | 52 | 130 |
| Sunflower | 65 | 36 | 54 |
| Silage corn | 177 | 69 | 177 |
| Soy | 0 | 46 | 52 |

Note: the considered variable costs in the ecological farming scenario entail costs for fertilization. Fertilization requirements are calculated according to nutrient removal (NPK requirement depending on average harvested yield minus field losses). Cost approach: net nutrient costs.
Source: Bayerische Landesanstalt für Landwirtschaft (2024)

**Table A5. Assumed factor demands for crops grown with mineral fertilizer, but without pesticides**

| **Factor demands** | **Working hours** per hectare | **Humus formation/degradation** Humus equivalent/hectare/year |
|---|---|---|
| Winter wheat | 8.8 | 100.00 |
| Rye and winter meslin | 8.19 | 100.00 |
| Winter barley | 8.68 | 100.00 |
| Spring barley | 8.4 | 100.00 |
| Oats | 8.03 | 100.00 |
| Triticale | 8.28 | 100.00 |
| Potatoes | 46.78 | -760.00 |
| Sugar beet | 175.2 | -760.00 |
| Winter rape | 8.86 | 100.00 |
| Silage corn | 11.62 | -560.00 |
| Soy | 13.87 | 600.00 |

Source: Verband Deutscher Landwirtschaftlicher Untersuchungs- und Forschungsanstalten (2014) and Kuratorium für Technik und Bauwesen in der Landwirtschaft e. V. (2023)

## Crop Rotational Model Constraints

**Table A6. Crop rotational constraints due to phytosanitary reasons**

| Crop | Cultivation break in years | Maximum % of arable land | Cause |
|---|---|---|---|
| Winter wheat | 2 | 33.3 | Fungal pathogens especially foot diseases, cereal cyst nematodes |
| Rye and winter meslin | 1-2 | 33.3-50 | Fungal pathogens especially foot diseases |
| Winter barley | 2-3 | 25-33.3 | Fungal pathogens especially foot diseases, cereal cyst nematodes, Thyphula, powdery mildew |
| Spring barley | 2 | 33.3 | Cereal cyst nematodes, powdery mildew |
| Oats | 3-5 | 16.7-25 | Cereal cyst nematodes |
| Triticale | 2-3 | 25-33.3 | |
| Potatoes | 3-4 | 20-25 | Potatoe cyst nematodes |
| Sugar beet | 4 | 20 | Fungal pathogens, Sugar beet cyst nematodes |
| Winter rape | 3-4 | 20-25 | Fungal pathogens, beet cyst nematodes, cabbage hernia |
| Sunflower | 6 | 14.3 | Fungal pathogens |
| Silage corn | 1-2 | 33.3-50 | |
| Soy | 3-4 | 20-25 | Fungal pathogens |

Source: modified after Kolbe (2008)

**Table A7. Relevant Common Agricultural Policy measures**

| GLÖZ (good agricultural and ecological condition of farmland) | |
|---|---|
| 7 | Crop rotation on arable land (suspended in 2023)<br>- on at least 33% of arable land different crop than in previous year<br>- on at least another 33% of the arable land crop rotation by:<br>  - other crop than in the previous year or<br>  - cultivation of a catch crop or greening by under sowing, change of the main crop in the third year at the latest.<br>- on the remaining arable land the main crop is changed in the third year at the latest.<br>Summer and winter crop of one type of crop are considered as two different crops.<br>For organic farms the requirements are considered to be fulfilled. |

Source: modified after Federal Ministry of Food and Agriculture (2021)

## Descriptive Statistics

**Table A8. Descriptive statistics of the variables yields (dt/ha), prices (€/dt) and variable costs (€/dt) of conventionally grown crops used for the simulation (without adjustment of trend and inflation)**

| | Winter wheat | Rye and winter meslin | Winter barley | Spring barley | Oats | Triticale | Pota-toes | Sugar beet | Winter rape | Silage maize | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Average yield | 68 | 61 | 51 | 49 | 62 | 87 | 294 | 690 | 35 | 452 | 35 |
| Variance | 57 | 70 | 50 | 40 | 110 | 382 | 6229 | 12374 | 54 | 3274 | 22 |
| SD | 7.58 | 8.36 | 7.06 | 6.30 | 10.51 | 19.56 | 78.92 | 111.24 | 7.31 | 57.22 | 4.74 |
| CV | 0.11 | 0.14 | 0.14 | 0.13 | 0.17 | 0.22 | 0.27 | 0.16 | 0.21 | 0.13 | 0.14 |
| Average price | 16 | 13 | 14 | 17 | 14 | 14 | 15 | 4 | 31 | 3 | 17 |
| Variance | 17 | 15 | 14 | 19 | 14 | 14 | 58 | 1 | 80 | 0 | 73 |
| SD | 4.11 | 3.82 | 3.71 | 4.33 | 3.75 | 3.79 | 7.65 | 0.78 | 8.95 | 0.49 | 8.54 |
| CV | 0.26 | 0.28 | 0.27 | 0.26 | 0.28 | 0.27 | 0.50 | 0.21 | 0.29 | 0.18 | 0.49 |
| Average variable costs | 665 | 676 | 505 | 639 | 605 | 508 | 433 | 596 | 2217 | 1345 | 697 |
| Variance | 14213 | 14192 | 6790 | 373 | 12853 | 8874 | 6599 | 5369 | 128434 | 1886 | 23035 |
| SD | 119.22 | 119.13 | 82.40 | 19.31 | 113.37 | 94.20 | 81.24 | 73.28 | 358.38 | 43.42 | 151.77 |
| CV | 0.18 | 0.18 | 0.16 | 0.03 | 0.19 | 0.19 | 0.19 | 0.12 | 0.16 | 0.03 | 0.22 |

Sources: yields: Statistische Ämter des Bundes und der Länder (2023) and Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (KTBL), https://www.ktbl.de/webanwendungen/standarddeckungsbeitraege; prices: Agrarmarkt Informations-Gesellschaft (AMI) (2010a, 2016, 2022) and Zentrale Markt- und Preisberichtstelle GmbH (ZMP) (2002, 2005). For soy, maize, sugar beets, and potatoes, the producer prices are sourced from KTBL; variable costs: Bayerische Landesanstalt für Landwirtschaft (LfL) https://www.lfl.bayern.de/index.php

**Table A9. Descriptive statistics of the observed variables yields (dt/ha), prices (€/dt) and variable costs (€/dt) of organically grown crops used for the simulation (without adjustment of trend and inflation)**

| | Winter wheat | Rye and winter meslin | Winter barley | Spring barley | Oats | Triticale | Pota-toes | Sugar beet | Sun flower | Silage maize | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Average yield | 41 | 34 | 36 | 34 | 37 | 40 | 238 | 500 | 22 | 404 | 25 |
| Variance | 12 | 12 | 35 | 67 | 12 | 12 | 987 | 3398 | 6 | 1226 | 24 |
| SD | 3.44 | 3.52 | 5.95 | 8.21 | 3.44 | 3.45 | 31.42 | 58.29 | 2.52 | 35.01 | 4.89 |
| CV | 0.08 | 0.10 | 0.17 | 0.24 | 0.09 | 0.09 | 0.13 | 0.12 | 0.11 | 0.09 | 0.20 |
| Average price | 35 | 31 | 29 | 41 | 32 | 28 | 49 | 27 | 64 | 5 | 64 |
| Variance | 51 | 58 | 43 | 36 | 50 | 38 | 121 | 5 | 36 | 0 | 351 |
| SD | 7.13 | 7.61 | 6.55 | 5.97 | 7.04 | 6.17 | 11.00 | 2.15 | 5.98 | 0.51 | 18.74 |
| CV | 0.20 | 0.25 | 0.22 | 0.14 | 0.22 | 0.22 | 0.23 | 0.08 | 0.09 | 0.10 | 0.29 |
| Average variable costs | 978.6 | 744.1 | 807.9 | 813 | 408.1 | 786.4 | 3163.9 | 2762 | 922.8 | 1681 | 934.6 |

Sources: yields: Bayerische Landesanstalt für Landwirtschaft (LfL), https://www.lfl.bayern.de/index.php; prices: AMI (2010b, 2013, 2023) and Bayerische Landesanstalt für Landwirtschaft (LfL), https://www.lfl.bayern.de/index.php; variable costs: Bayerische Landesanstalt für Landwirtschaft (LfL), https://www.lfl.bayern.de/index.php

## Correlations

**Table A10. Pairwise correlations of yields and producer prices of the conventional scenario**

| Variables | Winter wheat y | Rye y | Winter barley y | Spring barley y | Oats y | Triticale y | Pota-toes y | Sugar beet y | Winter rape y | Silage Corn y | Soy y | Winter wheat p | Rye p | Winter barley p | Spring barley p | Oats p | Triticale p | Pota-toes p | Sugar beet p | Winter rape p | Silage corn p | Soy p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat y | 1.000 | | | | | | | | | | | | | | | | | | | | | |
| Rye y | 0.667* | 1.000 | | | | | | | | | | | | | | | | | | | | |
| Winter barley y | 0.298 | 0.189 | 1.000 | | | | | | | | | | | | | | | | | | | |
| Spring barley y | 0.339 | 0.159 | 0.223 | 1.000 | | | | | | | | | | | | | | | | | | |
| Oats y | 0.820* | 0.730* | 0.388 | 0.131 | 1.000 | | | | | | | | | | | | | | | | | |
| Triticale y | 0.244 | 0.394 | 0.038 | -0.261 | 0.603* | 1.000 | | | | | | | | | | | | | | | | |
| Potatoes y | 0.078 | 0.168 | -0.143 | -0.005 | 0.293 | 0.710* | 1.000 | | | | | | | | | | | | | | | |
| Sugar beet y | 0.263 | 0.052 | 0.319 | -0.062 | 0.324 | 0.585* | 0.575* | 1.000 | | | | | | | | | | | | | | |
| Winter rape y | 0.802* | 0.531* | 0.198 | 0.224 | 0.569* | -0.024 | -0.195 | 0.044 | 1.000 | | | | | | | | | | | | | |
| Silage corn y | 0.205 | 0.012 | 0.374 | 0.344 | 0.272 | 0.363 | 0.430* | 0.704* | 0.030 | 1.000 | | | | | | | | | | | | |
| Soy y | -0.115 | 0.076 | 0.230 | -0.465* | -0.108 | 0.295 | 0.121 | 0.452* | -0.154 | -0.100 | 1.000 | | | | | | | | | | | |
| Winter wheat p | -0.489* | -0.485* | -0.124 | -0.401 | -0.362 | -0.018 | 0.104 | 0.059 | -0.332 | 0.096 | 0.220 | 1.000 | | | | | | | | | | |
| Rye p | -0.518* | -0.452* | -0.268 | -0.395 | -0.328 | 0.084 | 0.218 | 0.054 | -0.460* | 0.139 | 0.112 | 0.929* | 1.000 | | | | | | | | | |
| Winter barley p | -0.541* | -0.474* | -0.228 | -0.458* | -0.401 | -0.012 | 0.101 | 0.011 | -0.423* | 0.047 | 0.226 | 0.957* | 0.965* | 1.000 | | | | | | | | |
| Spring barley p | -0.366 | -0.335 | -0.236 | -0.442* | -0.220 | 0.080 | 0.178 | 0.092 | -0.309 | 0.148 | 0.161 | 0.893* | 0.952* | 0.933* | 1.000 | | | | | | | |
| Oats p | -0.487* | -0.388 | -0.226 | -0.435* | -0.281 | 0.143 | 0.210 | 0.022 | -0.387 | 0.058 | 0.205 | 0.937* | 0.959* | 0.950* | 0.924* | 1.000 | | | | | | |
| Triticale p | -0.543* | -0.436* | -0.263 | -0.427* | -0.391 | 0.024 | 0.126 | -0.045 | -0.400 | 0.012 | 0.199 | 0.957* | 0.953* | 0.982* | 0.905* | 0.959* | 1.000 | | | | | |
| Potatoes p | -0.118 | 0.157 | -0.073 | -0.206 | 0.136 | 0.003 | -0.165 | -0.361 | 0.063 | -0.163 | -0.042 | 0.483* | 0.536* | 0.532* | 0.600* | 0.563* | 0.561* | 1.000 | | | | |
| Sugar beet p | -0.237 | -0.157 | 0.203 | -0.197 | -0.309 | -0.187 | -0.375 | 0.075 | -0.309 | -0.177 | 0.378 | -0.199 | -0.241 | -0.120 | -0.278 | -0.288 | -0.202 | -0.374 | 1.000 | | | |
| Winter rape p | -0.593* | -0.528* | -0.227 | -0.404 | -0.423* | 0.032 | 0.313 | 0.100 | -0.524* | -0.005 | 0.256 | 0.889* | 0.836* | 0.835* | 0.774* | 0.831* | 0.829* | 0.310 | -0.158 | 1.000 | | |
| Silage corn p | -0.291 | -0.345 | -0.025 | -0.239 | -0.247 | -0.342 | -0.320 | -0.210 | -0.104 | -0.155 | -0.235 | 0.288 | 0.248 | 0.245 | 0.209 | 0.118 | 0.275 | 0.250 | -0.012 | 0.267 | 1.000 | |
| Soy p | -0.203 | -0.647* | 0.035 | 0.156 | -0.541* | -0.537* | -0.153 | 0.152 | -0.100 | 0.175 | 0.270 | 0.413 | 0.234 | 0.303 | 0.223 | 0.180 | 0.256 | -0.256 | 0.138 | 0.409 | 0.156 | 1.000 |

Note: y = yield, p = producer price, *p<0.05
Source: own calculations based on the data sources given in this text

**Table A11. Pairwise correlations of yields and producer prices of the organic farming scenario**

| Variables | Winter wheat y | Rye y | Winter barley y | Spring barley y | Oats y | Triticale y | Pota-toes y | Sugar beet y | Sun-flower y | Silage corn y | Soy y | Winter wheat p | Rye p | Winter barley p | Spring barley p | Oats p | Triticale p | Potatoe p | Sugar beet p | Sun-flower p | Silage corn p | Soy p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat y | 1.000 | | | | | | | | | | | | | | | | | | | | | |
| Rye y | -0.073 | 1.000 | | | | | | | | | | | | | | | | | | | | |
| Winter barley y | 0.293 | 0.084 | 1.000 | | | | | | | | | | | | | | | | | | | |
| Spring barley y | 0.207 | -0.447 | 0.014 | 1.000 | | | | | | | | | | | | | | | | | | |
| Oats y | 0.112 | 0.437 | 0.352 | -0.037 | 1.000 | | | | | | | | | | | | | | | | | |
| Triticale y | 0.247 | 0.342 | 0.161 | 0.306 | 0.257 | 1.000 | | | | | | | | | | | | | | | | |
| Potatoes y | 0.428 | 0.334 | 0.110 | -0.306 | 0.246 | 0.395 | 1.000 | | | | | | | | | | | | | | | |
| Sugar beet y | 0.612* | 0.013 | 0.534* | 0.068 | 0.207 | 0.377 | 0.281 | 1.000 | | | | | | | | | | | | | | |
| Sun-flower y | -0.652* | -0.066 | -0.302 | 0.188 | -0.213 | 0.025 | -0.320 | -0.516* | 1.000 | | | | | | | | | | | | | |
| Silage corn y | 0.567* | 0.030 | 0.302 | 0.418 | 0.065 | 0.339 | 0.172 | 0.546* | -0.262 | 1.000 | | | | | | | | | | | | |
| Soy y | -0.018 | 0.193 | 0.168 | 0.510* | 0.310 | 0.593* | 0.167 | -0.037 | 0.406 | 0.337 | 1.000 | | | | | | | | | | | |
| Winter wheat p | -0.187 | -0.505* | 0.225 | 0.252 | 0.128 | 0.052 | -0.075 | 0.198 | -0.006 | 0.015 | 0.182 | 1.000 | | | | | | | | | | |
| Rye p | 0.008 | -0.468 | 0.182 | 0.285 | 0.226 | 0.120 | -0.015 | 0.293 | 0.031 | 0.259 | 0.261 | 0.886* | 1.000 | | | | | | | | | |
| Winter barley p | -0.211 | -0.636* | 0.183 | 0.337 | -0.034 | -0.024 | -0.103 | 0.085 | 0.050 | 0.007 | 0.152 | 0.959* | 0.813* | 1.000 | | | | | | | | |
| Spring barley p | -0.156 | -0.394 | 0.122 | 0.157 | 0.270 | 0.126 | -0.169 | 0.235 | 0.059 | -0.083 | 0.202 | 0.859* | 0.873* | 0.727* | 1.000 | | | | | | | |
| Oats p | -0.018 | -0.613* | 0.170 | 0.341 | -0.128 | 0.038 | -0.060 | 0.283 | 0.039 | 0.198 | 0.082 | 0.843* | 0.811* | 0.869* | 0.629* | 1.000 | | | | | | |
| Triticale p | -0.195 | -0.580* | 0.236 | 0.306 | 0.088 | -0.020 | -0.083 | 0.074 | 0.034 | -0.028 | 0.178 | 0.966* | 0.842* | 0.985* | 0.765* | 0.853* | 1.000 | | | | | |
| Potatoes p | -0.573* | -0.099 | 0.124 | -0.083 | -0.259 | -0.055 | -0.065 | -0.204 | 0.564* | -0.090 | 0.238 | 0.401 | 0.297 | 0.481* | 0.175 | 0.491* | 0.451 | 1.000 | | | | |
| Sugar beet p | 0.283 | -0.178 | -0.078 | 0.607* | 0.160 | 0.609* | 0.233 | 0.298 | 0.177 | 0.494 | 0.539 | 0.309 | 0.480 | 0.345 | 0.181 | 0.535 | 0.291 | 0.177 | 1.000 | | | |
| Sun-flower p | -0.207 | -0.186 | -0.079 | 0.207 | 0.201 | 0.116 | -0.022 | -0.331 | 0.176 | -0.270 | 0.496* | 0.557* | 0.439 | 0.481* | 0.591* | 0.287 | 0.529* | 0.123 | 0.077 | 1.000 | | |
| Silage corn p | -0.186 | 0.014 | 0.022 | 0.313 | 0.275 | 0.686* | 0.187 | -0.072 | 0.414 | 0.069 | 0.403 | 0.368 | 0.517 | 0.372 | 0.478 | 0.411 | 0.417 | 0.240 | 0.501 | 0.009 | 1.000 | |
| Soy p | -0.116 | -0.090 | 0.400 | 0.158 | 0.547* | 0.218 | -0.109 | 0.050 | 0.168 | -0.155 | 0.372 | 0.423 | 0.396 | 0.353 | 0.552* | 0.112 | 0.431 | 0.100 | 0.304 | 0.436 | 0.421 | 1.000 |

Note: y = yield, p = producer price, * p<0.05

Source: own calculations based on the data sources given in this text

**Table A12. Pairwise correlations of yields and producer prices of the farming with mineral fertilizer, but without pesticides scenario**

| Variables | Winter wheat y | Rye y | Winter barley y | Spring barley y | Oats y | Triticale y | Pota-toes y | Sugar beet y | Sun-flower y | Silage corn y | Soy y | Winter wheat p | Rye p | Winter barley p | Spring barley p | Oats p | Triticale p | Pota-toes p | Sugar beet p | Sun-flower p | Silage corn p | Soy p |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat y | 1.000 | | | | | | | | | | | | | | | | | | | | | |
| Rye y | 0.667* | 1.000 | | | | | | | | | | | | | | | | | | | | |
| Winter barley y | 0.298 | 0.189 | 1.000 | | | | | | | | | | | | | | | | | | | |
| Spring barley y | 0.339 | 0.159 | 0.223 | 1.000 | | | | | | | | | | | | | | | | | | |
| Oats y | 0.820* | 0.730* | 0.388 | 0.131 | 1.000 | | | | | | | | | | | | | | | | | |
| Triticale y | 0.244 | 0.394 | 0.038 | -0.261 | 0.603* | 1.000 | | | | | | | | | | | | | | | | |
| Potatoes y | 0.078 | 0.168 | -0.143 | -0.005 | 0.293 | 0.710* | 1.000 | | | | | | | | | | | | | | | |
| Sugar beet y | 0.263 | 0.052 | 0.319 | -0.062 | 0.324 | 0.585* | 0.575* | 1.000 | | | | | | | | | | | | | | |
| Sunflower y | 0.802* | 0.531* | 0.198 | 0.224 | 0.569* | -0.024 | -0.195 | 0.044 | 1.000 | | | | | | | | | | | | | |
| Silage corn y | 0.205 | 0.012 | 0.374 | 0.344 | 0.272 | 0.363 | 0.430* | 0.704* | 0.030 | 1.000 | | | | | | | | | | | | |
| Soy y | -0.115 | 0.076 | 0.230 | -0.465* | -0.108 | 0.295 | 0.121 | 0.452* | -0.154 | -0.100 | 1.000 | | | | | | | | | | | |
| Winter wheat p | -0.489* | -0.485* | -0.124 | -0.401 | -0.362 | -0.018 | 0.104 | 0.059 | -0.332 | 0.096 | 0.220 | 1.000 | | | | | | | | | | |
| Rye p | -0.518* | -0.452* | -0.268 | -0.395 | -0.328 | 0.084 | 0.218 | 0.054 | -0.460* | 0.139 | 0.112 | 0.929* | 1.000 | | | | | | | | | |
| Winter barley p | -0.541* | -0.474* | -0.228 | -0.458* | -0.401 | -0.012 | 0.101 | 0.011 | -0.423* | 0.047 | 0.226 | 0.957* | 0.965* | 1.000 | | | | | | | | |
| Spring barley p | -0.366 | -0.335 | -0.236 | -0.442* | -0.220 | 0.080 | 0.178 | 0.092 | -0.309 | 0.148 | 0.161 | 0.893* | 0.952* | 0.933* | 1.000 | | | | | | | |
| Oats p | -0.487* | -0.388 | -0.226 | -0.435* | -0.281 | 0.143 | 0.210 | 0.022 | -0.387 | 0.058 | 0.205 | 0.937* | 0.959* | 0.950* | 0.924* | 1.000 | | | | | | |
| Triticale p | -0.543* | -0.436* | -0.263 | -0.427* | -0.391 | 0.024 | 0.126 | -0.045 | -0.400 | 0.012 | 0.199 | 0.957* | 0.953* | 0.982* | 0.905* | 0.959* | 1.000 | | | | | |
| Potatoes p | -0.118 | 0.157 | -0.073 | -0.206 | 0.136 | 0.003 | -0.165 | -0.361 | 0.063 | -0.163 | -0.042 | 0.483* | 0.536* | 0.532* | 0.600* | 0.563* | 0.561* | 1.000 | | | | |
| Sugar beet p | -0.237 | -0.157 | 0.203 | -0.197 | -0.309 | -0.187 | -0.375 | 0.075 | -0.309 | -0.177 | 0.378 | -0.199 | -0.241 | -0.120 | -0.278 | -0.288 | -0.202 | -0.374 | 1.000 | | | |
| Sunflower p | -0.593* | -0.528* | -0.227 | -0.404 | -0.423* | 0.032 | 0.313 | 0.100 | -0.524* | -0.005 | 0.257 | 0.889* | 0.836* | 0.835* | 0.774* | 0.831* | 0.829* | 0.310 | -0.158 | 1.000 | | |
| Silage corn p | -0.291 | -0.345 | -0.025 | -0.239 | -0.247 | -0.342 | -0.320 | -0.210 | -0.104 | -0.155 | -0.235 | 0.288 | 0.248 | 0.245 | 0.209 | 0.118 | 0.275 | 0.250 | -0.012 | 0.267 | 1.000 | |
| Soy p | -0.203 | -0.647* | 0.035 | 0.156 | -0.541* | -0.537* | -0.153 | 0.152 | -0.100 | 0.175 | 0.270 | 0.413 | 0.234 | 0.303 | 0.223 | 0.180 | 0.256 | -0.256 | 0.138 | 0.409 | 0.156 | 1.000 |

Note: y = yield, p = producer price, *p<0.05

Source: own calculations based on the data sources given in this text

## Contribution Margin Variances

**Table A13. Simulated contribution margin variances $(\sigma^2(CM)$ and covariances (cov(CM$_i$, CM$_k$)) of the 'conventional' farming scenario**

| Crops *i* | Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Winter rape | Silage corn | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | 61192 | | | | | | | | | | |
| Rye | 33579 | 45739 | | | | | | | | | |
| Winter barley | 31264 | 27008 | 51776 | | | | | | | | |
| Spring barley | 26959 | 23676 | 22994 | 38479 | | | | | | | |
| Oats | 38344 | 34336 | 19494 | 18195 | 46551 | | | | | | |
| Triticale | 47612 | 40373 | 33608 | 25233 | 51111 | 140402 | | | | | |
| Potatoes | 149457 | 145533 | 125400 | 103987 | 149164 | 378002 | 3493171 | | | | |
| Sugar beet | 616 | -1593 | -6645 | -9396 | 7503 | 36269 | 144364 | 381786 | | | |
| Winter rape | 48397 | 19590 | 12283 | 16611 | 31647 | 34739 | 56962 | 5806 | 90169 | | |
| Silage corn | 3197 | 1620 | -1151 | -3064 | 5099 | 16999 | 83690 | 26809 | 4156 | 110809 | |
| Soy | 9863 | -10293 | 19545 | 4104 | -13764 | -29960 | 14004 | -6403 | 2072 | -339 | 145275 |

Note: 'conventional' = conventional farming scenario with basic common agriculture policy restrictions
Source: own Monte Carlo simulation based on averages, and (co-)variances for yield, price and variable cost data

**Table A14. Simulated contribution margin variances $(\sigma^2(CM)$ and covariances (cov(CM$_i$, CM$_k$)) of the 'organic' farming scenario**

| Crops *i* | Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Sun-flower | Silage corn | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | 59488 | | | | | | | | | | |
| Rye | 36538 | 55013 | | | | | | | | | |
| Winter barley | 51771 | 34977 | 92171 | | | | | | | | |
| Spring barley | 54084 | 57293 | 62846 | 218296 | | | | | | | |
| Oats | 44030 | 36952 | 54995 | 79968 | 86094 | | | | | | |
| Triticale | 47602 | 38805 | 60746 | 69105 | 52578 | 81816 | | | | | |
| Potatoes | -3158 | 124884 | 221335 | 260925 | 218555 | 246133 | 8749242 | | | | |
| Sugar beet | 168593 | 38413 | 193621 | 289699 | 113967 | 112556 | -355213 | 2922886 | | | |
| Sunflower | 11456 | 18784 | 30780 | 45292 | 31642 | 38297 | 350987 | -90246 | 82091 | | |
| Silage corn | 14544 | 2502 | 8838 | 16212 | 4384 | 16560 | -52977 | 185852 | -3018 | 65992 | |
| Soy | 13467 | 11264 | 17700 | 69516 | 43158 | 36284 | 85348 | 92820 | 33927 | 19135 | 235746 |

Source: own Monte Carlo simulation based on averages, correlations and (co-)variances for yield, price and variable cost data

**Table A15. Simulated contribution margin variances $(\sigma^2(CM)$ and covariances (cov(CM$_i$, CM$_k$)) of the scenario 'no pesticides'**

| Crops *i* | Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Winter rape | Silage corn | Soy |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | 27709 | | | | | | | | | | |
| Rye | 18033 | 23147 | | | | | | | | | |
| Winter barley | 1349 | 12268 | 17521 | | | | | | | | |
| Spring barley | 16660 | 15416 | 12759 | 21232 | | | | | | | |
| Oats | 21966 | 20779 | 9495 | 12831 | 27751 | | | | | | |
| Triticale | 27012 | 24286 | 16235 | 17930 | 33034 | 89103 | | | | | |
| Potatoes | 53127 | 55754 | 37270 | 48008 | 61740 | 158347 | 858699 | | | | |
| Sugar beet | -98 | 348 | -2152 | -3586 | 3340 | 19221 | 48858 | 135857 | | | |
| Winter rape | 19044 | 8448 | 4326 | 7963 | 13945 | 14635 | 17575 | 547 | 25505 | | |
| Silage corn | 1903 | 1187 | -314 | -1515 | 3048 | 12763 | 39852 | 15305 | 1982 | 72469 | |
| Soy | 3336 | -3395 | 6454 | 3971 | -5503 | -11345 | 825 | -2103 | 225 | -568 | 35680 |

Note: 'No pesticides' = Farming without pesticides, but with mineral fertilizer
Source: own Monte Carlo simulation based on averages, and (co-)variances for yield, price and variable cost data

## Ceteris Paribus Analysis ‘Increased Soy Variance’

**Table A16. Optimized crop portfolio of the ‘conventional’ farming scenario when the soy variance is increased to 500000**

| Crops grown on hectare (ha) of arable land in the model farm | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Winter rape | Silage corn | Soy | Standard deviation σ(TCM) | Total contribu-tion margin (TCM) in Euro | Coefficient of variation (σ(TCM)/μ(TCM)) |
| 6 | 5 | 0 | 12 | 0 | 16 | 0 | 13 | 25 | 14 | 10 | 28284 | 60032 | 47% |
| 15 | 0 | 0 | 0 | 0 | 22 | 0 | 16 | 25 | 12 | 10 | 30000 | 64407 | 47% |
| 9 | 0 | 0 | 0 | 0 | 30 | 0 | 20 | 25 | 6 | 10 | 31623 | 67326 | 47% |
| 0 | 0 | 0 | 0 | 0 | 32 | 13 | 20 | 25 | 0 | 10 | 44721 | 77456 | 58% |
| 0 | 0 | 0 | 0 | 0 | 24 | 21 | 20 | 25 | 0 | 10 | 54772 | 82118 | 67% |
| 0 | 0 | 0 | 0 | 0 | 20 | 25 | 20 | 25 | 0 | 10 | 58332 | 84353 | 71% |

Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation

**Table A17. Optimized crop portfolio of the ‘organic’ farming scenario when the soy variance is increased to 500000**

| Crops grown on hectare (ha) of arable land in the model farm | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Sun-flower | Silage corn | Soy | Standard deviation σ(TCM) | Total contribu-tion margin (TCM) in Euro | Coefficient of variation (σ(TCM)/μ(TCM)) |
| 30 | 0 | 0 | 0 | 17 | 0 | 9 | 10 | 14 | 0 | 20 | 41231 | 295793 | 14% |
| 30 | 0 | 0 | 0 | 16 | 0 | 10 | 10 | 14 | 0 | 20 | 42426 | 301911 | 14% |
| 30 | 0 | 0 | 3 | 17 | 0 | 10 | 10 | 11 | 0 | 20 | 43589 | 306058 | 14% |
| 30 | 0 | 0 | 10 | 17 | 0 | 10 | 10 | 3 | 0 | 20 | 44721 | 306469 | 15% |
| 27 | 0 | 0 | 17 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 45826 | 30677 | 15% |
| 21 | 0 | 0 | 23 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 46904 | 307012 | 15% |
| 16 | 0 | 0 | 28 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 47958 | 307229 | 16% |
| 13 | 0 | 0 | 30 | 17 | 0 | 10 | 10 | 0 | 0 | 20 | 48437 | 307323 | 16% |

Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation

**Table A18. Optimized crop portfolio of the scenario ‘No pesticides’ when the soy variance is increased to 500,000**

| Crops grown on hectare (ha) of arable land in the model farm | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Winter wheat | Rye | Winter barley | Spring barley | Oats | Triticale | Potatoes | Sugar beet | Winter rape | Silage corn | Soy | Standard deviation σ(TCM) | Total contribu-tion margin (TCM) in Euro | Coefficient of variation (σ(TCM)/μ(TCM)) |
| 0 | 1 | 0 | 30 | 10 | 23 | 0 | 0 | 20 | 6 | 10 | 14491 | 29963 | 48% |
| 0 | 0 | 0 | 30 | 10 | 25 | 0 | 0 | 20 | 5 | 10 | 14832 | 30795 | 48% |
| 0 | 0 | 0 | 24 | 17 | 25 | 0 | 0 | 20 | 4 | 10 | 15042 | 30943 | 49% |

Note: ‘No pesticides’ = farming with mineral fertilizer, but without pesticides
Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation

## Humus Formation and Working Hours

**Table A19. Humus formation/degradation and total working hours of optimized crop portfolio of the farming scenario ‘conventional’**

| Standard deviation of the total contribution margin (σ(TCM)) | Humus formation/degradation Humus equivalent/year | Total working hours per year |
|---|---|---|
| 17321 | -283 | 996 |
| 20000 | -1706 | 1006 |
| 22361 | -2988 | 1008 |
| 24495 | -3714 | 1066 |
| 26458 | -5766 | 1122 |
| 28284 | -8313 | 1171 |
| 30000 | -10509 | 1214 |
| 31623 | -12494 | 1252 |
| 44721 | -21156 | 1539 |
| 54772 | -26646 | 1739 |
| 63246 | -28700 | 1816 |

Note: ‘conventional’ = conventional farming scenario with basic common agriculture policy restrictions.
The model farm has in total 100 hectares.
Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation

**Table A20. Humus formation/degradation and total working hours of optimized crop portfolio of the farming scenario ‘organic’**

| Standard deviation of the total contribution margin (σ(TCM)) | Humus formation/degradation Humus equivalent/ /year | Total working hours per year |
|---|---|---|
| 40000 | 11245 | 3249 |
| 41231 | 10961 | 3279 |
| 42426 | 10800 | 3295 |
| 43589 | 10800 | 3297 |
| 44721 | 10800 | 3309 |
| 45826 | 10800 | 3327 |
| 47333 | 10800 | 3348 |

Note: ‘organic’ = organic agriculture. The model farm has in total 100 hectares.
Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation

**Table A21. Humus formation/degradation and total working hours of optimized crop portfolio of the farming scenario ‘No pesticides’**

| Standard deviation of the total contribution margin (σ(TCM)) | Humus formation/degradation Humus equivalent/year | Total working hours per year |
|---|---|---|
| 14142 | 5763 | 865 |
| 14491 | 6356 | 863 |
| 14832 | 6889 | 860 |
| 15166 | 7414 | 858 |
| 15492 | 8240 | 854 |
| 15811 | 10000 | 844 |
| 16125 | 10000 | 841 |
| 16432 | 10000 | 838 |
| 16442 | 10000 | 838 |

Note: ‘No pesticides’ = Farming with mineral fertilizer, but without pesticides.
The model farm has in total 100 hectares.
Source: own optimization with Quadratic Risk Programming based on simulated contribution margins from own Monte Carlo simulation