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Improving a dynamic farm level model by coupling empirically estimated pre-crop values with crop rotation optimization

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The dominance of cereal-based rotations in Finnish agriculture contributes to adverse environmental impacts, and shifting towards diversified cropping systems has been minimal. Since economic viability and profit motives are strong among farmers, there is a need for analysis tools investigating profitability of agronomically feasible, diversified cropping systems and rotations. While there is consensus on pre-crop effects, their impact is unclear and often overlooked in decision-making. We integrate recent empirically estimated pre-crop values into farm models to assess their influence on land use and farm economy and use dynamic optimization to solve the economically optimal crop rotations. The results show that including empirically estimated pre-crop values improves on subjective expert estimates of pre-crop effects and can eliminate the need for additional rotational constraints. Utilizing pre-crop effects consistently over time may lead to significant economic gains. This approach can contribute to sustainable agriculture by encouraging diversification and resilience, even amidst changing climates or novel crops.

Key words: farm management, diversification, dynamic optimization, land use, crop sequencing, agricultural economics

Introduction

Agriculture contributes significantly to greenhouse gas (GHG) emissions globally, as well as to the loss of landscape diversity, natural habitats, species diversity, and to damages to soil and water ecosystems (Campbell et al. 2017, IPCC 2019). Several adverse environmental impacts of agriculture, such as depletion of soil nutrients and reducing the risk caused by pests and diseases, are attributable to monotonous crop sequencing and land use (Kirkegaard et al. 2008, Lin 2011, Rosa-Schleich et al. 2019). Diversification of crop rotations, by utilizing a high number of different types of crops, likely provides multiple benefits by reducing these impacts (Kremen and Miles 2012, Lechenet et al. 2014, Rosa-Schleich et al. 2019).

The concept of crop rotation, i.e. system of raising crops in a regular order one after the other on the same field parcel, is dynamic rather than fixed (Peltonen-Sainio et al. 2020), and may vary a lot on how many different crops are cultivated. Diversification of crop rotations has been included in the Common Agricultural Policy (CAP) objectives since 2000 as part of the voluntary agricultural environmental schemes. Despite the past efforts to use of more diverse crop choices and rotations, impacts on biodiversity have been minor at best in European countries (Mills et al. 2020, Gütschow et al. 2021). In Finland, monotonous crop rotations and the strong dominance of only a few major cereal species (Peltonen-Sainio et al. 2017) as well as soil degradation caused by soil compaction and reduction in carbon stocks (Heikkinen et al. 2013) have probably contributed to stagnating yields and high yield gaps (Peltonen-Sainio et al. 2015, Schils et al. 2018). On the other hand, this means that there is still lots of unexploited potential to diversify agricultural land use (Peltonen-Sainio et al. 2016, Peltonen-Sainio and Jauhiainen 2019) and to benefit from the various ecosystem services that such transition may provide in the short and long run (EASAC 2022).

Since economic viability and profit motives are strong among farmers in the context of sustainable land use and production choices (e.g., Gütschow et al. 2021), there is a need for analysis tools investigating the profitability of agronomically feasible, diversified cropping systems and rotations. While static optimization approaches have been applied in farm management (Galán-Martín et al. 2015, Monjardino et al. 2022), dynamic whole-farm modelling, including comprehensive land use and nutrient-use descriptions, has been considered important when analyzing improvements in sustainability of farming systems (Berntsen et al. 2003, Dueri et al. 2007, Chardon et al. 2012). These dynamic cropping system models have been utilized in evaluating effects of different rotations on soil nitrogen balances and resulting yield impacts as well as climate change impacts on farming systems (Dueri et. al. 2007, Schönhart et al. 2011, 2018).

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There is a consensus about pre-crop effects, i.e., that the preceding crops in rotations have various impacts on the following crop and its yield, but the effects have been mostly unknown and, hence, ignored in farmer's decision making (Kirkegaard et al. 2008). There is a consensus that monotonous crop sequencing causes yield losses in a short term for example due to increased pest and disease risks, but also in the long-term as arable intensification with monocultures has resulted in deterioration of soils due to loss of organic matter, erosion, compaction, and contamination with pesticides (Stoate et al. 2001, Baldwin 2006, Bennett et al. 2012). Earlier, pre-crop effects have been studied in field trials (e.g. Sieling and Christen 2015, Babublicová 2016), and according to these studies, yield losses can be avoided, and yields can even be improved by using more diverse crop rotations.

Although farm scale crop rotation decisions have been analysed a lot (e.g., Maynard et al. 1997, Hennessy 2006, Meyer-Aurich et al. 2006, Dury et al. 2012), only a small volume of literature has tried to incorporate pre-crop effects in optimization problems or simulation models. For example, Guinet et al. (2020) aimed to quantify and understand the effect of grain legume compared to cereal pre-crops using an agronomic model (STICS) to calculate nitrogen mineralization from pre-crop residues and nitrogen leaching between pre-crop harvest and wheat harvest. In addition, Hoffman et al. (2018) utilized a widely used agro-ecosystem model APSIM (Holzworth et al. 2014) to examine nitrogen management in crop rotations after the break-up of grassland. Especially economic modelling of explicit dynamics and decision making of crop rotation at farm and field parcel scale, over several years, remain few.

Several papers studying crop rotation with dynamic optimization as well as farm management modelling assume yield effects based on monotonous crop sequencing and diverse crop rotations (Liu et al. 2016, Purola et al. 2018, Purola and Lehtonen 2020). However, without sound empirical basis for the pre-crop effects there might be a need to have additional constraints in models to prevent solutions considered unrealistic or infeasible. Recently, Peltonen-Sainio et al. (2019) introduced a novel method for estimation of the pre-crop values based on Sentinel 2 satellite data on 238 290 field parcels on Finnish farms. Thereby, the pre-crop impacts estimated comprehensively represent the current crop production systems and conditions in the prime crop production regions of Finland.

The aim of this paper is to show what is the value and contribution of pre-crop effects on farm management and economy. Pre-crop effects provide more information to a farmer than the expert estimates on monocultural yield losses and thus one may expect significant changes in farm management and economy. We integrate the pre-crop values in the farm model and analyze the resulting differences in the land use and farm economy, i.e., how farm management is changed due to increased information, and how a farmer may optimally utilize the novel understanding on the pre-crop effects when designing crop rotations. In this paper, we extend an earlier published dynamic optimization farm model (Purola and Lehtonen 2020) with empirically estimated pre-crop values (Peltonen-Sainio et al. 2019). We show how using empirically estimated pre-crop values in dynamic farm modelling adds more information and thus eliminates the need for subjective expert estimates of monocultural yield losses, other subjective pre-crop values, or any additional constraints. The results show how and to what extent a farmer may benefit from utilizing the pre-crop value information in farm management in the long run. Eventually, using pre-crop values may lead to more realistic and valuable results in farmers' decision making.

Model and methods

Utilizing dynamic optimization framework allows us to combine crop production and farm economics with various technical data and response functions, such as crop yield response to nitrogen levels, effects of liming and fungicide treatments. Parameters of the input use effects on crop yields are based on empirical estimations. Accounting for the effects of crop rotation on crop yields, simultaneously with input use effects, is an important economic issue at the farm level.

We maximize net present value with 6% interest rate over 30-year time horizon. 6% interest rate is close to stock markets annual yield during the last 100 years (Pörssisäätiö 2023), and 30-year time span is of a relevant length in terms of farmers' careers. It is also long enough to show long-term effects.

Denoting the interest rate with *r*¸and the discount factor with *b = 1/(1+r)*, the optimization problem is as follows:

$$\max_{A_{tpi},N_i,L_{tp},F_{tp}} \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{n} b^t\left(\mu_i Y_{tpi}(\ldots)+S_i-C_{tpi}(\ldots)\right)A_{tpi}-\theta\sum_{y=1}^{T}\sum\nolimits_c\sum\nolimits_c b^y A'XA \quad (1)$$

subject to

$$C_{tpi} = V_i + G_p + c_L\left(L_{tp}\right) + c_F\left(F_{tp}\right) + c_N\left(N_i\right) \tag{2}$$

$$Y_{tpi} = \hat{Y}_i\left(\alpha_i\left(N_i, L_{tp}, F_{tp}\right)\left(1+\beta_{ij}\right)A_{t-1,p,j} + \sum_{d=t-5}^{t}\gamma_i A_{dpi}\right) \tag{3}$$

$$\sum_{p=1}^{P}\sum_{i=1}^{n} A_{pit} = 1 \;\forall\; t\,, \tag{4}$$

where A_{tpi} is land allocation of crop i at time t on parcel p, N_i is nitrogen fertilization of crop i, L_{tp} is the use of liming at time t on field parcel p, and F_{tp} is the fungicide use at time t on parcel p. μ_i is the unit price of crop i, Y_{tpi} the yield of crop i on parcel p at time t, and S_i depicts the agricultural subsidies for crop i. θ denotes the risk aversion of the farmer, and X the covariance matrix of crop specific gross margins. C_{tpi} denotes the costs of crop i at time t on parcel p where V_i and G_p denote the variable and logistic costs, c_L, c_F and c_N the costs of liming, fungicide, and nitrogen fertilization respectively.

$\hat{Y}_i$ denotes the baseline level of yields for crop i, α_i the crop-specific effects of nitrogen use (N), liming (L) and fungicide (F) on yield on parcel p at time t, β_{ij} the pre-crop value (or yield-effects in cases NP and NP+LC) of crop j on crop i, and γ_i the yield losses from monoculture. Due to different time scales (1 year vs. 5 years), yield or pre-crop effects and monoculture losses are separate coefficients. Finally, T is the length of the time horizon, P the number of parcels, and n the total number of crops.

The optimization problem presented by eqs. 1–4 was solved using nonlinear programming using the CONOPT 3 solver of the General Algebraic Modelling System (GAMS) software. Typical time to solve the problem is under 10 seconds.

For numerical optimization we utilized a dynamic farm-level model DEMCROP, which was used to simulate farm economics and management of a representative 10-parcel farm located in Southwestern Finland. Farms in the region have average size of 59 hectares, focusing on cereal-based crop rotation with about 70% of farm-area allocated on cereals (Peltonen-Sainio and Jauhiainen 2019, OSF 2021). The model has been applied before in various settings in Lehtonen et al. (2014), Liu et al. (2016), Purola et al. (2018) and Purola and Lehtonen (2020).

In the DEMCROP-model, farmer's management decisions include land-use management decision for all field parcels, liming, fertilization, and fungicide use. Crop yield is dependent on the use of nitrogen fertilizer and fungicides at the current year, as well as on the soil pH. Nitrogen fertilization decision is based on fertilizer and crop prices through non-nitrogen response function of crop-specific yields: nitrogen fertilization is increased until the value of marginal yield gain from fertilizer is equal to the price of fertilizer. Nitrogen fertilization, considered necessary for all crops except for fallow and nature managed field (NMF), is the same for each crop in all field parcels, and each year is independent, i.e. crop selection or fertilization use has no effect on the crop selection or fertilization need next year. However, fungicide use is not a necessity but is determined based on fungicide response function for wheat and barley in all field parcels separately. Crop yields are also dependent on soil pH, which in turn can be controlled via liming activity. The effect of soil pH on yield is calculated by multiplying the difference between the soil pH and crop specific optimal pH (Table A1) by 0.12 (Purola et al. 2018). The level of liming and fungicide use activities, as well as crop choice, are optimized for each field parcel. We set risk aversion coefficient theta to 0.000001 based on Purola and Lehtonen (2020). This small risk-aversion parameter means low risk aversion and is compatible with the literature, which suggests that farmers in developed countries are typically relatively little risk averse (Raskin and Cochran 1986) though some risk behavior can be observed. Nevertheless, risk aversion plays little role in this study.

Crop yields are also dependent on land use of the previous year at each field parcel, based on the pre-crop effect. The model also considers greenhouse gas emissions for different land-use using the calculation scheme also used by Purola and Lehtonen (2022) based on the approach of the official national GHG inventory (Statistics Finland 2021) compatible to the IPCC methodology and coefficients.

In this paper the model is extended to account for the effect of the preceding crop on yields of crops sown at subsequent years, using empirically estimated pre-crop values (Peltonen-Sainio et al. 2019). In Peltonen-Sainio et al. (2019) values are presented over two years, and here we utilize the mean of the values. In this paper, we use six crop options (spring and winter wheat, feed and malting barley, oats, and rapeseed), as well as two forms of set-aside (fallow, nature managed field [NMF]). These are the main cultivars in the region, accounting for over 80% of total cultivated area between 2010 and 2020 (OSF 2021). Rapeseed was found to be the most beneficial pre-crop for all crops followed by barley. Winter wheat was found more beneficial before barley than spring wheat while oats appeared to decrease barley yields if grown as pre-crop. Nature management fields can benefit winter wheat and rapeseed as a following crop, while they can lead to yield reduction when followed by barley or oats. Similarly, fallow seems to favor the yields of winter and spring wheat as well as rapeseed if they are following.

There is one unit of farmland available that is split into 10 equally large and shaped parcels. The distance of the parcels to the farm center varies between 0 and 7 km. Distance of each parcel affects the logistic costs related to that parcel (Table A2). All parcels are assumed to be on mineral soil. Initial yields ($\hat{Y}_i$) for each are calculated as average yields from the region between 2000 and 2018 from official farm statistics (OFS 2021). Pre-crop values (β_{ij}), i.e. the effects of preceding crops on the yield of the next crop grown at the same parcel of land, are based on Peltonen-Sainio et al. (2019), and are presented in Table 1. Yield penalties for monoculture cultivation (γ_i), calculated over 5 years, were set to –5% p.a. for cereals and –20% p.a. for rapeseed for case Pre-crop. These yield penalties based on expert assessment are necessary since the pre-crop effects of Peltonen-Sainio et al. (2019) consider only one-year pre-crop effects, while it is known that long-term monocultures do result in deterioration of soils.

Table 1. Pre-crop values for each crop combination, applied in case Pre-crop, based on Peltonen-Sainio et al. (2019). Positive values mean yield gains, negative yield losses, and zero no effect.

	Preceding crop							
Current crop	Spring wheat	Winter wheat	Feed barley	Malting barley	Spring oats	Rapeseed	Fallow	Nature managed field (NMF)
Spring wheat	0.0 %	3.0 %	6.8 %	6.8 %	0.1 %	7.5 %	4.4 %	0.5 %
Winter wheat	1.3 %	0.0 %	6.1 %	6.1 %	4.9 %	8.8 %	3.3 %	9.4 %
Feed barley	-0.7 %	1.6 %	0.0 %	0.0 %	-1.5 %	4.9 %	-2.7 %	-4.5 %
Malting barley	-0.7 %	1.6 %	0.0 %	0.0 %	-1.5 %	4.9 %	-2.7 %	-4.5 %
Oats	3.8 %	3.0 %	5.9 %	5.9 %	0.0 %	5.3 %	0.5 %	-2.6 %
Rapeseed	5.8 %	5.2 %	7.2 %	7.2 %	5.4 %	0.0 %	4.9 %	9.5 %
Fallow	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
NMF	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %

Especially rapeseed-specific pests and diseases may stay in soil even 4–5 years and it is not sufficient to consider only one-year effects of oilseed monocultures. Hence the monoculture-driven yield losses over 5 years based on expert estimates also used by Purola and Lehtonen (2020) are used in the model and presented in Table 2.

Table 2. Yield effects based on expert estimates (Purola and Lehtonen 2020), applied in cases NP and NP+LC

	Preceding crop							
Current crop	Spring wheat	Winter wheat	Feed barley	Malting barley	Spring oats	Rapeseed	Fallow	NMF
Spring wheat	-5 %	-5 %	-5 %	-5 %	-4 %	0 %	0 %	0 %
Winter wheat	-5 %	-5 %	-5 %	-5 %	-4 %	0 %	0 %	0 %
Feed barley	-5 %	-5 %	-5 %	-5 %	-4 %	0 %	0 %	0 %
Malting barley	-5 %	-5 %	-5 %	-5 %	-4 %	0 %	0 %	0 %
Spring oats	-4 %	-4 %	-4 %	-4 %	-5 %	0 %	0 %	0 %
Rapeseed	0 %	0 %	0 %	0 %	0 %	-35 %	0 %	0 %
Fallow	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
NMF	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %

To see how the model economically performs under different assumptions, we analyze three different model specifications:

1. no pre-crop values, but with cumulative yield effects over 5 years and minimal land-use constraints (NP)

2. no pre-crop values, but with cumulative yield effects over 5 years and extensive land-use constraints (NP+LC) (c.f. Purola and Lehtonen 2020)

3. pre-crop values over 1 year with cumulative monocultural yield losses over 5 years and minimal land-use constraints (Pre-crop)

For each of these cases we find the solution maximizing the net present value subject to crop rotation, liming, nitrogen fertilization, and fungicide use.

For cases NP and NP+LC, only monoculture effects are accounted for in the yield effects, thus (γ_i) is set to 0. Total yield effects in these cases are as in Purola and Lehtonen (2020) and are presented in Table 2. For case Pre-crop we assume yield effects both from pre-crop values as well as from monocultural cultivation.

All land use constraints, both minimal and extensive, are based on agricultural subsidy (CAP) requirements: with minimal land-use constraint there is lower and upper limits on the share of nature managed field and fallows. With extensive land-use constraints the model is prevented from growing e.g. extreme monocultures and instead directed towards slightly more diverse rotations as specified in the CAP greening conditions (EC 2021), even if they may be economically inferior. The detailed description of all land constraints is presented in Appendix 1. The extensive land use constraints also rule out some most likely infeasible crop rotations, e.g. winter cereals may not be possible to be sown after oats or rapeseed requiring late harvesting times.

Average variable costs and subsidies per crop are based on DREMFIA sector model used e.g. analysis in Lehtonen and Niemi (2018) and outputs reported in official statistics over 15 years (from 2000 to 2018) (OSF 2021). These parameter values are presented in Table A1 in Annex, and cost functions for liming, fungicide use, and nitrogen fertilization are presented in Table A3.

Results

Under case NP (no pre-crop values considered) with cumulative yield losses and minimal constraints, the optimal crop rotation consists predominantly of malting barley, with mainly rapeseed and nature managed fields as break crops (Fig. 1). On average, about 70% of the total area is allocated to malting barley, 15% on rapeseed and 10% on nature managed field (Fig. 2). This, while being the optimal solution, is not practically feasible. Including more restricting land-use constraints (case NP+LC), changes the optimal crop rotation into a much more diverse solution (Fig. 1). In this case the model allocated on average 50% of the land on malting barley, 20% of the land on spring wheat, 20% on rapeseed and nature managed field, and 5% on oats (Fig. 2). Finally, extending the model to pre-crop values and minimal land use constraints adds more diversity to the crop rotation solution (Fig. 1), with about 33% of land-area used on average on malting barley, 22% on both spring and winter wheat, 12% on rapeseed, 5% on oats, and 5% on nature managed field (Fig. 2). These land use share of total cereals area is already quite close to the aggregate average of the region (considering all production lines, not only crop farms), 63% (73% if not considering grasslands) (OSF 2021). The share of total cereals on crop farms is higher than the average of the whole region.

While both feed barley and fallow were options in the model, neither was optimal to choose in any of the scenarios. This is because malting barley is more profitable than feed barley (Table A1), yet has the same yield-effects (Table 1). Similarly, nature managed field (NMF) accrues higher subsidies, and has high pre-crop effects when followed by winter wheat or rapeseed (Table 1). This can be seen in the results between the models as well: in the case NP+LC, as there are no pre-crop values and thus no significant differences in the yield effects between the cereals, NMF is quite often followed by malting barley (Fig. 1). However, when the model is extended to utilize pre-crop values, NMF is most often followed by winter wheat, utilizing the high pre-crop benefits to obtain higher yields.

Comparing the results between the cases NP and NP+LC, differences in average crop yields per parcel are only minor (Fig. 3). This is because the effects of preceding crops between the cases are identical, and those are minimized in the optimization in both cases. Compared to the average observed yields over 2000–2018 in the region (Purola and Lehtonen 2020), the crop yields under the first two cases are few percentages lower. This is because in these two cases we only consider the negative effects of crop rotation, the cumulative monocultural yield losses. Enabling pre-crop values in the model (case Pre-crop), however, results in higher crop yields than with cases NP and NP+LC, as well as with the observed yields. The higher crop yields of the case Pre-crop compared to e.g. with NP+LC are mainly because of the positive short-run (one-year) pre-crop values; optimization is very efficient in utilizing the pre-crop values, resulting in higher yields. As expected, differences in net present values among all three cases are similar to that of yields (Fig. 4), being highest in the case Pre-crop. It is noteworthy that while the optimal crop rotations between the cases NP and NP+LC are very different, the differences between the net present values are only small.

Annual greenhouse gas emissions per ton of crop production are presented in Figure 5. The emissions for cases NP and NP+LC are on average around 1 ton of CO_2eq per ton of crop production, while for the case Pre-crop for every ton of crop produced approximately 1.2 tons of CO_2eq are emitted. This difference in the GHG emissions is explained mostly due to higher N_2O emissions from fertilization. Compared to cases NP and NP+LC, in case Pre-crop, crop production is more focused on spring and winter wheat (Fig. 2), which both require significantly larger amounts of fertilizer (Table A2). Thus, the CO_2eq emissions are larger in case Pre-crop than in cases NP and NP+LC (Fig. 5).

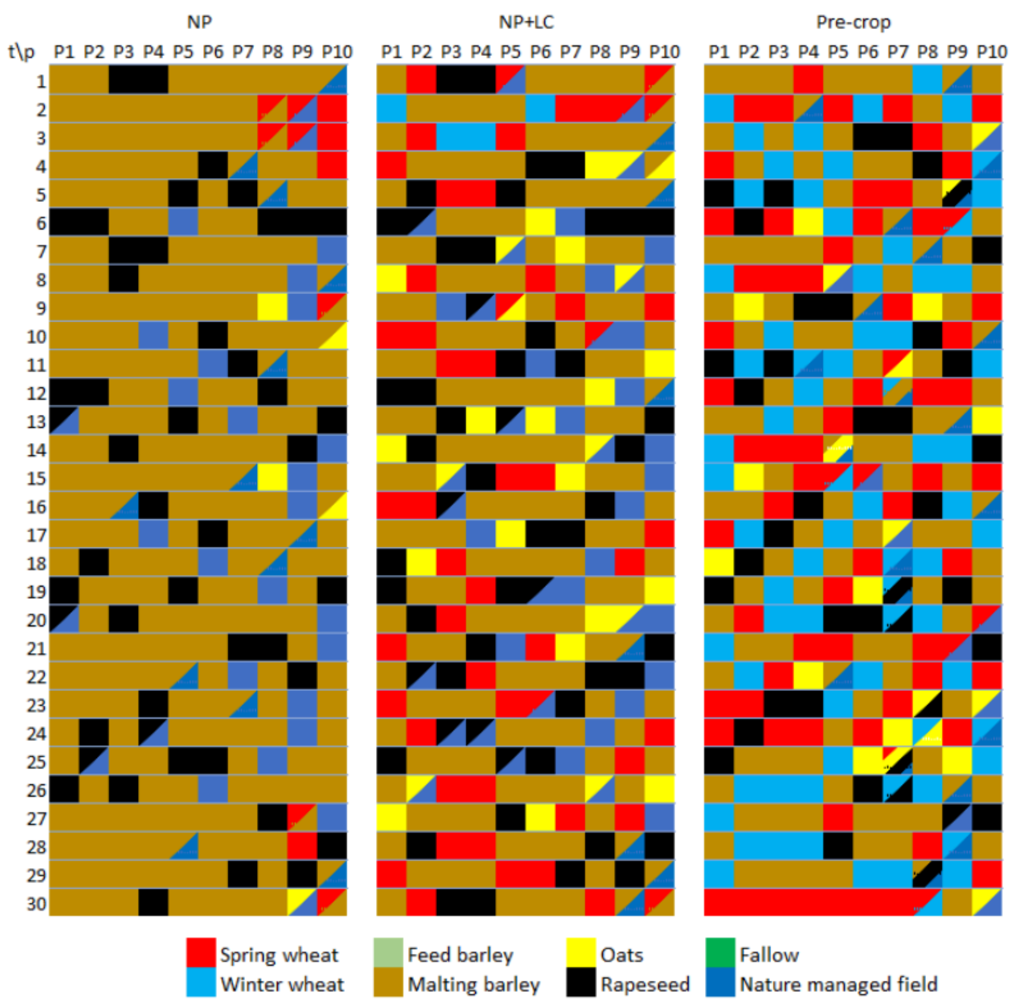

Fig. 1. Optimal crop rotation with no pre-crop values and minimal land-use constraints (NP), no pre-crop values with extensive land-use constraints (NP+LC), and pre-crop values with minimal land-use constraints (Pre-crop). P1–P10 are the different parcels, 1 being the closest to farm center and 10 the furthest, and 1 to 30 are the years.

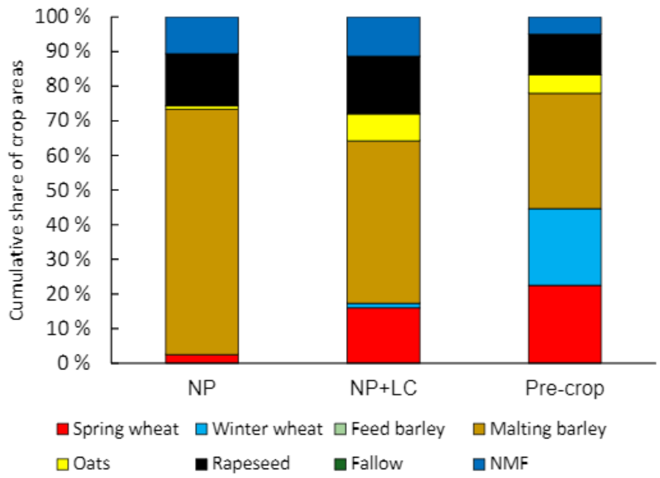

Fig. 2. Average shares of each crop on total farm area for each of the cases. Analyzed cases: no pre-crop values and minimal land-use constraints (NP), no pre-crop values with extensive land-use constraints (NP+LC), and pre-crop values with minimal land-use constraints (Pre-crop).

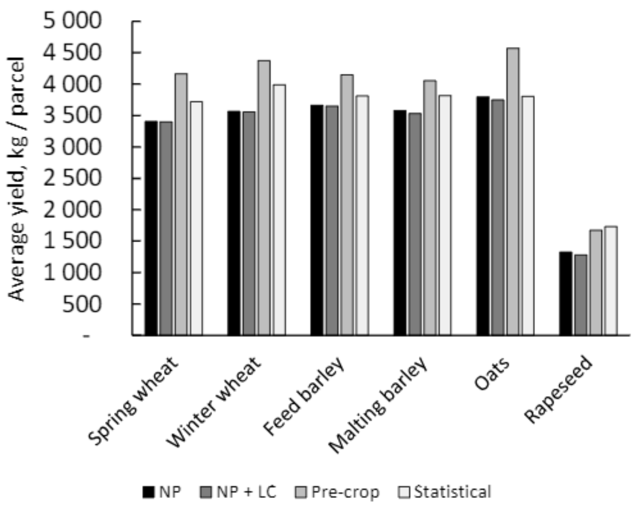

Fig. 3. Average calculated crop yields over all parcels in each scenario, and crop yields from official statistics. Analyzed cases: no pre-crop values and minimal land-use constraints (NP), no pre-crop values with extensive land-use constraints (NP+LC), and pre-crop values with minimal land-use constraints (Pre-crop).

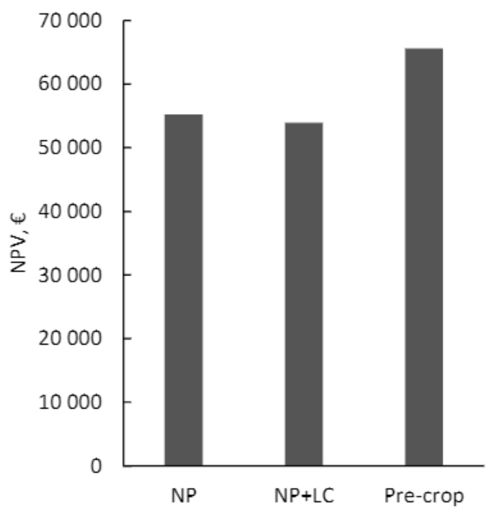

Fig. 4. Net present value (NPV, €) of each case. 6% interest rate, 30-year time horizon. Analyzed cases: no pre-crop values and minimal land-use constraints (NP), no pre-crop values with extensive land-use constraints (NP+LC), and pre-crop values with minimal land-use constraints (Pre-crop).

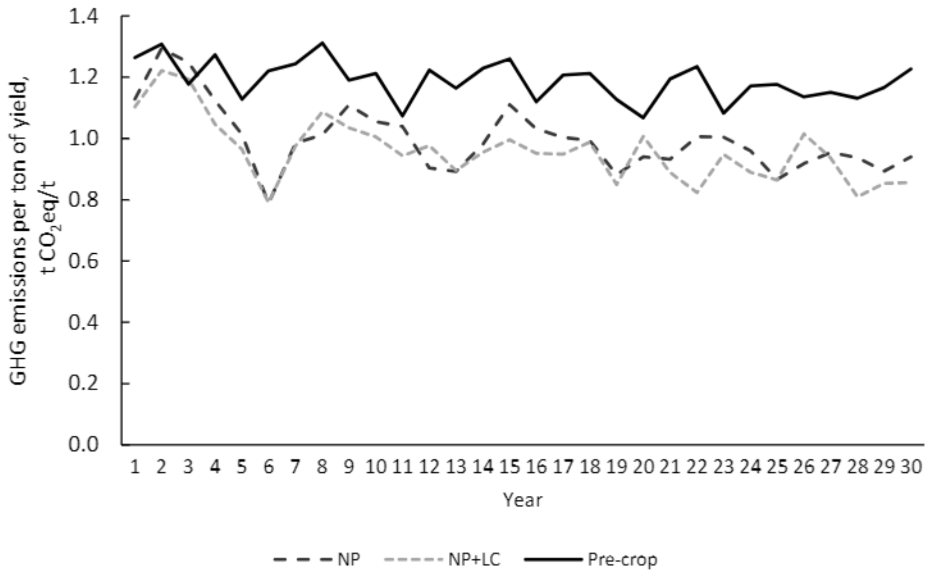

Fig. 5. Annual greenhouse gas emissions per ton of total harvest for cases NP, NP+LC, and Pre-crop. Basis for the calculations is the official national GHG inventory (Statistics Finland 2021) compatible to the IPCC methodology and coefficients. Cases: no pre-crop values and minimal land-use constraints (NP), no pre-crop values with extensive land-use constraints (NP+LC), and pre-crop values with minimal land-use constraints (Pre-crop).

Discussion

Recent empirical estimations on pre-crop effects (Peltonen-Sainio et al. 2019) enable their integration into agricultural models and crop rotation optimization. Changes in crop rotation have dynamic consequences in land use and crop management over several years, and each crop affects the next ones in rotation. Per our results, utilizing the pre-crop values optimally can result in significant economic gains in the long-term. Farmers should focus on crop rotations and benefits of pre-crop values rather than focus on individual crops and their management in a static setting which hides dynamic consequences. Our results showed that in general, utilizing pre-crop values in decision making also eliminates the need for additional constraints such as specific rules on which crop sequences are feasible.

So far, optimal crop rotation analyses have assumed cumulative monocultural yield losses based on expert judgment (Purola et al. 2018, Purola and Lehtonen 2020, 2022). For example, per expert estimates, monocultures cause some yield losses, particularly by increasing risks of pests and diseases, which are exacerbated due to climate change. Hence, such monocultural yield losses can be avoided by cultivating different crops in a sequence (Jalli et al. 2021). While these assumptions are reasonable, there remains uncertainty in the magnitude of monocultural yield losses which may accumulate over time (Purola and Lehtonen 2020). Furthermore, without sound empirical basis for the monocultural yield loss coefficients, there might be a need to add additional constraints to prevent unrealistic or infeasible solutions. These constraints in addition impose lost market revenue from the most profitable crops, malting barley in our case. While the share of malting barley is significantly lower in case NP+LC compared to the case NP, the difference in NPV is relatively small, as the profitability of wheat is almost as good as that of malting barley. The use of empirically estimated pre-crop values makes the model more robust and reduces or eliminates the need to rely on subjective expert estimates of yield losses or additional constraints, thus these losses of revenue are avoided as well.

In this paper, we show that by combining empirically estimated pre-crop values in crop rotation optimization allows us to loosen the land-use constraints specific to certain crop sequences, and still obtain diverse crop rotation solutions and feasible results for the region. For example, to avoid unrealistic results and obtain results closer to typical land use in the region, Purola and Lehtonen (2020) uses constraints to avoid sowing winter cereals after oats or rapeseed due to possible late maturing of oats or rapeseed which may risk sufficient development of winter cereals before winter. In addition, no malting barley was allowed after malting barley or feed barley because of the cultivation recommendations (VYR 2012, 2014). In this paper, case NP+LC, uses similar constraints. However, while imposing these constraints led to model solutions much closer (compared to case NP) to typical or average land use in the region, and thus were crucial for applying the model prior extending to pre-crop values, they also limit the applicability of the model for more complex questions. Expert estimates emphasize the role of break crops, and other synergies, such as positive yield effects of winter wheat, are largely ignored, thus the results differ from the case Pre-crop. This suggests that the magnitude of the pre-crop effects is unclear and utilized suboptimally also in expert estimates.

One challenge that the pre-crop values introduce is their effect on the covariance matrix. In our study, risk aversion was assumed to be at very low levels, so we assumed that rational economic decision-making only considers historical covariation of profits between crops. Introducing the effects of pre-crop yield changes on the covariation of profits would be difficult and would require a farmer to also consider the effects of crop rotation on the future covariation of profits between crops. This optimization problem becomes quite complex. It is an interesting issue to be considered in future studies with higher risk aversion.

Rodriguez et al. (2021) found, when they utilized data from field trials and questionnaire, that more diverse crop rotations result in lower profitability in several cases that were considered. This seemingly contradicts our result on improved profitability when utilizing pre-crop values optimally in case where pre-crop values are utilized. Therefore, this may imply that although the utilization of pre-crop values optimally results in higher profits, farmers might lack knowledge or information on the most efficient previous and subsequent crop combinations in rotation. Rodriguez et al. (2021) reported that one of the main obstacles to diversification is the lack of economic incentives. However, our findings show that the main economic incentive is the increased yields for several crops resulting from pre-crop value utilization. Because of the pre-crop values, it is economically beneficial to cultivate even less-profitable break crops to obtain higher yields the following year (Kirkegaard et al. 2008).

In this paper we chose to focus on the main crops in the region. While many minor crops have excellent pre-crop values, this paper focuses on the methodological aspects of utilizing empirically estimated pre-crop values in optimization. In addition, the availability of e.g. crop price data, makes including more minor crops challenging. This is also reflected in Rodriguez et al. (2021), where the lack of market demand affected the profitability. By limiting the crop selection to major crops, we can relatively safely assume stable market prospects.

However, the question of market demand becomes an important aspect if the farm model -based analysis is extended to minor crops with significant pre-crop values, e.g. grain legumes, potatoes (*Solanum tuberosum* L.), sugar beet (*Beta vulgaris* var. *altissima* L.) or caraway (also included in the pre-crop values of Peltonen-Sainio et al. 2019). While in single farm the pre-crop effect is difficult to observe due to various differences between the parcels, the method developed to estimate pre-crop values from high number of farmers' fields makes it possible to have data to cover more years and regions (Peltonen-Sainio et al. 2019). This makes it possible to include minor crops when optimizing the crop rotations which may provide interesting results and insights for farmers and value chains, but also to consider the contribution of regional differences to farm profitability. Introducing new crops, especially those that fix nitrogen in the soil, such as legumes, would also require the model to be extended to account for this 'inherited' nitrogen in the fertilization optimization.

We reach similar crop rotation diversity whether we apply the model with pre-crop values and minimal land-use constraints, or only monocultural yield losses and extensive land-use constraints. While the pre-crop effects are utilized in also traditional practices to some extent, the difference between optimal results and observed (Fig. 3) suggests that the utilization of these values in decision making is most likely suboptimal. Our results show that farmers could attain more value by utilizing the pre-crop effects optimally in their farm management and decision making. Thus, the analysis presented responds to the need of qualified tools and assistance for cropping diversification and crop rotations, called for by e.g. farmers in Sweden (Rodriguez et al. 2021).

Utilizing extensive land-use constraints may limit the applicability of the model to wider issues. Since using pre-crop values in optimization results in realistic solutions without additional land use constraints, this approach enables the study to tackle more diverse questions. Such situations include changed prices or subsidies, or changed productivity due to climate change, climate change adaptation through e.g. new crop cultivars (see e.g. Purola et al. 2018), or climate change mitigation.

Conclusions

This study developed a dynamic optimization farm model capable of accounting for pre-crop effects, i.e. a yield gain or loss of a crop if certain other crops were cultivated prior. With this integration, we can abolish the land-use constraints preventing infeasible or non-recommended crop rotation solutions applied in earlier papers and gain significant economic gains if they are aware of and utilize pre-crop effects consistently over several years. The economic gains are, however, conditional, among other things, on the prices of agricultural commodities, discount rate and current policy conditions. Utilizing pre-crop effects may also contribute to land diversification towards sustainable and resilient agriculture.

Compared to earlier approaches in the literature, this kind of dynamic modelling brings agricultural economics closer to the specific agronomy of cropping diversification and rotation. It can be used in various studies specific on adaptation to climate change via crop rotations and new crop cultivars, in studies specific on soil organic carbon when data are available on crop specific soil carbon effects, and in studies specific on soil improvements, with sensitivity analysis related to market price and agricultural policy changes.

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References

Babulicová, M. 2016. Enhancing of winter wheat productivity by the introduction of field pea into crop rotation. Agriculture (Pol'nohospodárstvo) 62: 101–110. https://doi.org/10.1515/agri-2016-0011

Baldwin, K.R. 2006. Crop rotations on organic farms. Centre for Environmental Farming Systems (CEFS), North Carolina Cooperative Extension Service.

Bennett, A.J., Bending, G.D., Chandler, D., Hilton, S. & Mills, P. 2012. Meeting the demand for crop production: the challenge of yield decline in crops grown in short rotations. Biological Reviews 87: 52–71. https://doi.org/10.1111/j.1469-185X.2011.00184.x

Berntsen, J., Petersen, B.M., Jacobsen, B.H., Olesen, J.E. & Hutchings, N.J. 2003. Evaluating nitrogen taxation scenarios using the dynamic whole farm simulation model FASSET. Agricultural Systems 76: 817–839. https://doi.org/10.1016/S0308-521X(02)00111-7

Campbell, B.M., Beare, D.J., Bennett, E.M., Hall-Spencer, J.M., Ingram, J.S., Jaramillo, F. & Shindell, D. 2017. Agriculture production as a major driver of the Earth system exceeding planetary boundaries. Ecology and Society 22. https://doi.org/10.5751/ES-09595-220408

Chardon, X., Rigolot, C., Baratte, C., Espagnol, S., Raison, C., Martin-Clouaire, R., Rellier, J.P., Le Gall, A., Dourmad, J.Y., Piquemal, B., Leterme, P., Paillat, J.M., Delaby, L., Garcia, F., Peyraud, J.L., Poupa, J.C., Morvan, T. & Faverdin, P. 2012. MELODIE: a whole-farm model to study the dynamics of nutrients in dairy and pig farms with crops. Animal 6: 1711–1721. https://doi.org/10.1017/S1751731112000687

Dury, J., Schaller, N., Garcia, F., Reynaud, A. & Bergez, J.E. 2012. Models to support cropping plan and crop rotation decisions. A review. Agronomy for Sustainable Development 32: 567–580. https://doi.org/10.1007/s13593-011-0037-x

Dueri, S., Calanca, P.L. & Fuhrer, J. 2007. Climate change affects farm nitrogen loss-A Swiss case study with a dynamic farm model. Agricultural Systems 93: 191–214. https://doi.org/10.1016/j.agsy.2006.05.005

EASAC 2022. Regenerative Agriculture in Europe. A critical analysis of contributions to European Union Farm to Fork and Biodiversity Strategies. EASAC Policy Report 44. 58 p. ISBN: 978-3-8047-4372-4. www.easac.eu

EC 2021. Sustainable land use (greening). https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/income-support/greening_en

Galán-Martín, Á., Pozo, C., Guillén-Gosálbez, G., Vallejo, A.A. & Esteller, L.J. 2015. Multi-stage linear programming model for optimizing cropping plan decisions under the new Common Agricultural Policy. Land Use Policy 48: 515–524. https://doi.org/10.1016/j.landusepol.2015.06.022

Guinet, M., Nicolardot, B. & Voisin, A.S. 2020. Nitrogen benefits of ten legume pre-crops for wheat assessed by field measurements and modelling. European Journal of Agronomy 120: 126151. https://doi.org/10.1016/j.eja.2020.126151

Gütschow, M., Bartkowski, B. & Felipe-Lucia, M.R. 2021. Farmers' action space to adopt sustainable practices: a study of arable farming in Saxony. Regional Environmental Change 21:103. https://doi.org/10.1007/s10113-021-01848-1

Heikkinen, J., Ketoja, E., Nuutinen, V. & Regina, K. 2013. Declining trend of carbon in Finnish cropland soils in 1974-2009. Global Change Biology 19: 1456–1469. https://doi.org/10.1111/gcb.12137

Hennessy, D.A. 2006. On monoculture and the structure of crop rotations. American Journal of Agricultural Economics 88: 900–914. https://doi.org/10.1111/j.1467-8276.2006.00905.x

Hoffmann, M.P., Isselstein, J., Rötter, R.P. & Kayser, M. 2018. Nitrogen management in crop rotations after the break-up of grassland: Insights from modelling. Agriculture, Ecosystems & Environment 259: 28–44. https://doi.org/10.1016/j.agee.2018.02.009

Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G. & Keating, B.A. 2014. APSIM-evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software 62: 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

IPCC 2019. Climate Change and Land: an IPCC special report on climate change, desertifcation, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. Summary for Policymakers

Jalli, M., Huusela, E., Jalli, H., Kauppi, K., Niemi, M., Himanen, S. & Jauhiainen, L. 2021. Effects of Crop Rotation on Spring Wheat Yield and Pest Occurrence in Different Tillage Systems: A Multi-Year Experiment in Finnish Growing Conditions. Frontiers in Sustainable Food Systems 5: 647335. https://doi.org/10.3389/fsufs.2021.647335

Kirkegaard, J., Christen, O., Krupinsky, J. & Layzell, D. 2008. Break crop benefits in temperate wheat production. Field Crops Research 107: 185–195. https://doi.org/10.1016/j.fcr.2008.02.010

Kremen, C. & Miles, A. 2012. Ecosystem services in biologically diversified versus conventional farming systems: benefits, externalities, and trade-offs. Ecology and Society 17. https://doi.org/10.5751/ES-05035-170440

Lechenet, M., Bretagnolle, V., Bockstaller, C., Boissinot, F., Petit, M., Petit, S. & Munier-Jolain, N.M. 2014. Reconciling pesticide reduction with economic and environmental sustainability in arable farming. PloS one 9: e97922. https://doi.org/10.1371/journal.pone.0097922

Lehtonen, H., Liu, X. & Purola, T. 2014. Endogenising yield development through management and crop rotation decisions in dynamic farm level modeling. In: 24. Jahrestagung der Österreichischen Gesellschaft für Agrarökonomie, Universität für Bodenkultur Wien 25.-26. September 2014. Tagungsband 2014: 13–14.

Lehtonen, H. & Niemi, J. 2018. Effects of reducing EU agricultural support payments on production and farm income in Finland. Agricultural and Food Science 27: 124–137. https://doi.org/10.23986/afsci.67673

Lin, B.B. 2011. Resilience in agriculture through crop diversification: Adaptive management for environmental change. Bioscience 61: 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Liu, X., Lehtonen, H., Purola, T., Pavlova, Y., Rötter, R. & Palosuo, T. 2016. Dynamic economic modelling of crop rotations with farm management practices under future pest pressure. Agricultural Systems 144: 65–76. https://doi.org/10.1016/j.agsy.2015.12.003

Maynard, L.J., Harper, J.K. & Hoffman, L.D. 1997. Impact of risk preferences on crop rotation choice. Agricultural and Resource Economics Review26: 106–114. https://doi.org/10.1017/S1068280500000873

Meyer-Aurich, A., Weersink, A., Janovicek, K. & Deen, B. 2006. Cost efficient rotation and tillage options to sequester carbon and mitigate GHG emissions from agriculture in Eastern Canada. Agriculture, Ecosystems & Environment 117: 119–127. https://doi.org/10.1016/j.agee.2006.03.023

Mills, J., Ingram, J., Dibari, C., Merante, P., Karaczun, Z., Molnar, A. & Ghaley, B.B. 2020. Barriers to and opportunities for the uptake of soil carbon management practices in European sustainable agricultural production. Agroecology and Sustainable Food Systems 44: 1185–1211. https://doi.org/10.1080/21683565.2019.1680476

Monjardino, M., Loi, A., Thomas, D.T., Revell, C.K., Flohr, B.M., Llewellyn, R.S. & Norman, H.C. 2022. Improved legume pastures increase economic value, resilience and sustainability of crop-livestock systems. Agricultural Systems 203: 103519. https://doi.org/10.1016/j.agsy.2022.103519

OSF 2021. Official Statistics of Finland (OFS), 2021. Statistical database. Agricultural Statistics. https://www.luke.fi/en/statistics/about-statistics/statistics-database

Peltonen-Sainio, P., Jauhiainen, L. & Latukka, A. 2020. Interactive tool for farmers to diversify high-latitude cereal-dominated crop rotations. International Journal of Agricultural Sustainability 18: 319–333. https://doi.org/10.1080/14735903.2020.1775931

Peltonen-Sainio, P., Salo, T., Jauhiainen, L., Lehtonen, H. & Sieviläinen, E. 2015. Static yields and quality issues: Is the agri-environment program the primary driver? Ambio 44: 544–556. https://doi.org/10.1007/s13280-015-0637-9

Peltonen-Sainio, P., Jauhiainen, L. & Lehtonen, H. 2016. Land use, yield and quality changes of minor field crops: Is there superseded potential to be reinvented in northern Europe? PLOS ONE. https://doi.org/10.1371/journal.pone.0166403

Peltonen-Sainio, P., Jauhiainen, L. & Sorvali, J. 2017. Diversity of high-latitude agricultural landscapes and crop rotations: increased, decreased or back and forth? Agricultural Systems 154: 25–33. https://doi.org/10.1016/j.agsy.2017.02.011

Peltonen-Sainio, P. & Jauhiainen, L. 2019. Unexploited potential to diversify monotonous crop sequencing at high latitudes. Agricultural systems 174: 73–82. https://doi.org/10.1016/j.agsy.2019.04.011

Peltonen-Sainio, P., Jauhiainen, L., Honkavaara, E., Wittke, S., Karjalainen, M. & Puttonen, E. 2019. Pre-crop values from satellite images for various previous and subsequent crop combinations. Frontiers in Plant Science 10: 462. https://doi.org/10.3389/fpls.2019.00462

Purola, T. & Lehtonen, H. 2020. Evaluating profitability of soil-renovation investments under crop rotation constraints in Finland. Agricultural Systems 180: 102762. https://doi.org/10.1016/j.agsy.2019.102762

Purola, T., Lehtonen, H., Liu, X., Tao, F. & Palosuo, T. 2018. Production of cereals in northern marginal areas: An integrated assessment of climate change impacts at the farm level. Agricultural Systems 162: 191–204. https://doi.org/10.1016/j.agsy.2018.01.018

Purola, T. & Lehtonen, H. 2022. Farm-Level Effects of Emissions Tax and Adjustable Drainage on Peatlands. Environmental Management 69: 154–168. https://doi.org/10.1007/s00267-021-01543-1

Pörssisäätiö 2023. Sijoituskohteet ja niiden valinta. https://www.porssisaatio.fi/sijoituskoulu/sijoituskohteet-valintakriteerit/ (in Finnish).

Raskin, R. & Cochran, M.J. 1986. Interpretations and transformations of scale for the Pratt-Arrow absolute risk aversion coefficient: Implications for generalized stochastic dominance. Western Journal of Agricultural Economics 11: 204–210.

Rodriguez, C., Dimitrova Mårtensson, L.M., Zachrison, M. & Carlsson, G. 2021. Sustainability of Diversified Organic Cropping Systems-Challenges Identified by Farmer Interviews and Multi-Criteria Assessments. Frontiers in Agronomy 75. https://doi.org/10.3389/fagro.2021.698968

Rosa-Schleich, J., Loos, J., Mußhof, O. & Tscharntke, T. 2019. Ecological-economic trade-offs of diversifed farming systems - A review. Ecological Economics 160: 251–263. https://doi.org/10.1016/j.ecolecon.2019.03.002

Schils, R., Olesen, J.E., Kersebaum, K.-C., Rijk, B., Oberforster, M., Kalyada, V., Khitrykau, M., Gobin, A., Kirchev, H., Manolova, V., Manolov, I., Trnka, M., Hlavinka, P., Palosuo, T., Peltonen-Sainio, P., Jauhiainen, L., Lorgeou, J., Marrou, H., Danalatos, N., Archontoulis, S., Fodor, N., Spink, J., Roggero, P.P., Bassu, S., Pulina, A., Seehusen, T., Uhlen, A.K., Żyłowska, K., Nieróbca, A., Kozira, J., Silva, J.V., Maçãs, B.M., Coutinho, J., Ion, V., Takáč, J., Mínguez, I., Eckersten, H., Levy, L., Herrera, J.M., Hiltbrunner, J., Kryvobok, O., Kryvoshein, O., Silvester-Bradley, R., Kindred, D., Topp, C.F.E., Boogaard, H., de Groot, H., Lesschen, J.P., Van Bussel, L., Wolf, J., Zijlstra, M., Van Loon, M. & Van Ittersum, M. 2018. Cereal yield gaps across Europe. European Journal of Agronomy 101: 109–120. https://doi.org/10.1016/j.eja.2018.09.003

Schönhart, M., Schmid, E. & Schneider, U.A. 2011. CropRota - a crop rotation model to support integrated land use assessments. European Journal of Agronomy 34: 263–277. https://doi.org/10.1016/j.eja.2011.02.004

Schönhart, M., Trautvetter, H., Parajka, J., Blaschke, A.P., Hepp, G., Kirchner, M., Mitter, H., Schmid, E., Strenn, B. & Zessner, M. 2018. Modelled impacts of policies and climate change on land use and water quality in Austria. Land Use Policy 76: 500–514. https://doi.org/10.1016/j.landusepol.2018.02.031

Sieling, K. & Christen, O. 2015. Crop rotation effects on yield of oilseed rape, wheat and barley and residual effects on the subsequent wheat. Archives of Agronomy and Soil Science 61: 1531–1549. https://doi.org/10.1080/03650340.2015.1017569

Statistics Finland 2021. Greenhouse gas emissions in Finland 1990 to 2019. National Inventory Report under the UNFCCC and the Kyoto Protocol Submission to the European Union. 15 March 2021.

Stoate, C., Boatman, N.D., Borralho, R.J., Carvalho, C.R., De Snoo, G.R. & Eden, P. 2001. Ecological impacts of arable intensification in Europe. Journal of environmental management 63: 337–365. https://doi.org/10.1006/jema.2001.0473

VYR 2012. Opas rypsin ja rapsin viljelyyn (Guide for turnip rape and oilseed rape cultivation). Vilja-alan yhteistyöryhmä 2012. http://vyr.fi/multimagazine/web/rypsin_rapsin_opas/fi/

VYR 2014. Opas mallasohran viljelyyn (Guide for malting barley cultivation). Viljaalan yhteistyöryhmä 2012 (updated 2014). http://vyr.fi/multimagazine/web/mallasohraopas/fi/

Appendices

Table A1. Parameter values applied in numerical analysis. Sources: Unit prices are long-term average farm gate prices of crops in Finland over 2000–2018, crop yields are average yields observed in the South-West Finland 2000–2018 (OSF 2021). The average variable costs and subsidies of the crops specific for South-West Finland are derived from a recent updated version of a dynamic multi-regional sector model of Finnish agriculture (DREMFIA) (Lehtonen and Niemi 2018), which relies on validated approximations of the average use of inputs per crop in each region. Optimal pH and fungal disease losses are based on Purola et al. (2018) and Purola and Lehtonen (2020).

	Unit price, p_i € / kg	Baseline yields, $\bar{Y}$ kg / ha	Variable costs, V_i € / ha	Subsidies, S_i € / ha	Baseline gross margin, € / ha	Optimal pH	Fungal disease losses %
Spring Wheat	0.148	3788	580	650	631	6.5	5.85 %
Winter Wheat	0.148	4193	610	695	706	6.5	5.85 %
Feed Barley	0.128	3884	527	563	533	6.1	6.26 %
Malting Barley	0.153	3885	589	635	640	6.5	6.26 %
Oats	0.123	3877	510	563	530	6.1	0 %
Rapeseed	0.285	1731	587	705	611	6.1	0 %
Fallow	0	0	244	390	146	-	0 %
NMF	0	0	264	554	290	-	0 %

Table A2. Logistical costs for each parcel (Purola and Lehtonen 2020).

Parcel	Logistical costs, €
1	1.115
2	1.115
3	2.23
4	2.23
5	4.46
6	4.46
7	8.92
8	11.15
9	13.38
10	15.61

Table A3. Liming, fungicide use, and nitrogen fertilization cost functions (Purola et al. 2018, Purola and Lehtonen 2020)

	Cost function
Liming	$c_L = 32.7525L_{tp} - 0.685L_{tp}^{\ 2}$
Fungicide	$c_F^{Barley} = 34F_{tp}$ $c_F^{Wheat} = 52F_{tp}$
Fertilization	$c_N = 1.5N_i$

Table A4. Optimal nitrogen use. Source: Purola et al. 2020, adjusted for South-West Finland as in Purola and Lehtonen 2020.

	Optimal nitrogen use, N_i kg ha^{-1}
Spring Wheat	110
Winter Wheat	140
Feed Barley	90
Malting Barley	90
Oats	90
Rapeseed	100
Fallow	0
Nature Managed Field	0

Appendix 1

Land-use constraints applied in each of the scenarios in detail. The constraints applied are based on CAP agricultural subsidy requirements and cultivation recommendations (VYR 2012, 2014)

NP:

Fallow + NMF minimum of 5% of total land area.

Max 75% of total area on single crop.

Winter wheat cannot be cultivated after oats or rapeseed, as they have no time to root after these late-maturing crops.

NP + LC:

Fallow + NMF minimum of 5% of total land area.
Max 75% of area on single crop.
Any combination of two crops can be max of 75% of land area.
Malting barley cannot be cultivated on single parcel in subsequent years.
Winter wheat cannot be cultivated after oats or rapeseed, as they have no time to root after these late-maturing crops.

Pre-crop:

Fallow + NMF minimum of 5% of total land area.
Max 75% of area on single crop.
Winter wheat cannot be cultivated after oats or rapeseed, as they have no time to root after these late-maturing crops.