# Ex-ante assessment of policies supporting precision agriculture in small-scaled farming systems

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## Abstract

Reducing nitrogen losses and the associated negative impact on the environment is a major challenge in agricultural production. Precision agricultural technologies are supposed to help solving this challenge. Since the adoption rate of such technologies in small-scale farming systems is still rather low, additional policy measures are needed to support their adoption. In this study, we investigate the efficiency of such measures using an agent-based modelling framework that combines cognitive and dispositional farmers' characteristics with a bio-economic optimization model. We simulate the effect of different policies on the adoption decisions of farmers in a Swiss case study. We use census, choice experiment and survey data from Swiss crop farmers to calibrate the agent-based model. Our results help to better assess the impact of different policy measures on the adoption decisions regarding site-specific fertilization and to inform policy makers on the most efficient measures.

**Keywords** precision farming, technology adoption, agent-based modelling, variable rate technologies

**JEL code** Q16, Q18

## Introduction

Improvements in nitrogen use efficiency and the associated reduction of negative environmental impacts due to nitrogen losses, is one of the main challenges in agricultural production. Precision agriculture technologies are expected to help address this challenge by providing timely, detailed, and site-specific production information (Schimmelpfennig and Ebel, 2016). Although technologies for site-specific nitrogen application have been available on the market for several years, their application rate in small-scale European farm systems is lower than expected (e.g., Finger et al., 2019; Lowenberg-DeBoer and Erickson, 2019; Groher et al., 2020; Späti et al., 2022). Besides the low profitability, behavioral factors might be an explanation for the low adoption rate (Barnes et al., 2019a, b). Farmers' individual cognitive, social, and dispositional factors also affect the uptake of sustainable farming technologies (Dessart et al., 2019). This is of specific importance if policy measures are implemented to incentivize the adoption of site-specific nitrogen fertilization technologies and thus increase nitrogen use efficiency in agriculture.

In this study, we simulate farmers' adoption decisions regarding precision agricultural technologies using an agent-based modelling approach to quantify the environmental and economic effect of policy measures designed to support the adoption of site-specific nitrogen fertilization technologies. More specifically, we assess and compare how a nitrogen tax and different forms of subsidies (i.e., for nitrogen reduction, for technology use and an area payment) influence adoption decisions for variable rate technologies taking into account farmers' individual social, cognitive and dispositional factors. To this end, we combine survey, choice experiment and census data of 418 farmers (Späti et al., 2022) with a bio-economic model (Späti et al., 2021) in an agent-based modelling framework (Huber et al., 2021). This allows us to simulate the emerging efficiency and effectiveness of various policy measures based on the adoption decision of heterogeneous farmers in small-scaled farming systems.

Previous research has addressed the adoption of precision agriculture technologies in recent years (e.g., Aubert et al., 2012; Barnes et al., 2019a , b; Blasch et al., 2021; Schimmelpfennig, 2016; Tey and Bindal, 2012). However, such farm-level studies often do not consider the individual decision-making of heterogeneous farmers. Agent-based models (ABMs) allow to capture the heterogeneity of actors and to model the interactions between agents (Zhang & Vorobeychik, 2019). They therefore offer a way to contribute to a better understanding of adoption decisions and the diffusion of such technologies. Agent-based modeling approaches have been increasingly used in recent years for conducting ex-post and ex-ante evaluations of agricultural policies (Huber et al., 2018). However, little research has been done on the impact of potential policy measures to increase nitrogen use efficiency considering the heterogeneity of farm and farmers' characteristics (e.g., cognitive, social, and dispositional factors). Additionally, current ABMs are not well linked to empirical evidence on the adoption and diffusion of precision farming at the farm level and thus do not have a sufficient empirical basis (Shang et al., 2021).

In this paper, we aim to fill this gap by combining empirical census, survey, and choice experiment data with an agent-based modelling approach for an ex-ante assessment of different policy measures (i.e., tax on nitrogen, subsidy technology, or direct payment) aiming to increase nitrogen use efficiency in small-scaled farming systems, focussing on wheat production systems in Switzerland. We simulate the effect of farmers individual and heterogeneous adoption decisions of site-specific nitrogen fertilization technologies in wheat production under different policy settings and quantify the total nitrogen reduction due to the adoption of the technologies as well as the efficiency of the policy measure (i.e., Fr./kg N saved). The considered policy scenarios include 1) a tax on nitrogen use (CHF/kg), 2) payment for reduced nitrogen (CHF/kg), 3) fixed payment (subsidy) for the application of the technology (CHF/farm) and 4) Subsidy for each ha, which is managed with the technology (CHF/ha). Our simulation set up is structured in four steps. First, we calculate the change in gross margins for wheat production on each farm for four different technologies that provide information on nitrogen availability with increasing spatial resolutions (i.e., section control, satellite imagery, handheld sensor, and drone). The calculations are based on a bio-economic model (Späti et al., 2021) calibrated to our sample using farm census data. Secondly, we calculate gross margins on each farm in the four policy scenarios and with varying spatial heterogeneity of the underlying fields. Thirdly, we use the agent-based modelling framework FARMIND (Huber et al., 2022) to simulate the farmers' individual adoption decision in these scenarios taking into account farmers' willingness to pay and willingness to accept these technologies. More specifically, we exploit the findings from a choice experiment which shows that farmers' request for compensation when reducing nitrogen input is higher than their willingness to pay for the same amount of nitrogen input. Furthermore, we also consider farmers' risk preferences, their preferences for technologies and attitudes towards environment, and production and their tendency for socially oriented behaviour i.e., the observation of their peers and the imitation of their successful adaptation decisions. Fourthly, we simulate the adoption decisions of each individual farmer with increasing tax and subsidy levels with the goal to reduce the overall nitrogen input of all farms to 10, 15 and 20%. Since, within the framework of the future development of Swiss agricultural policy, the loss of nitrogen from Swiss agriculture shall be reduced by 20% until 2030 (BLW, 2021). This allows to calculate the effectiveness of the different nitrogen reduction policies and to compare their efficiency.

Our results show given the differences in the perceived costs and benefits of the four technologies and the heterogenous characteristics of the farmers, a tax scheme might be the most efficient policy to reduce nitrogen input in our case study region. Subsidies for technology uptake or per area have a much lower efficiency than policy schemes focusing on nitrogen input directly. Our analysis adds to the existing literature by showing how individual behavioural components influence the adoption of precision agriculture technologies and to what extent this affects the efficiency of different policy incentives.

The remainder of this paper is organized as follows. First, we introduce the case study and provide an overview of the different variable-rate technologies included in our analysis. We then present the methodology used for our analysis, followed by some results and conclusions.

## Background

The case study region covers the two Cantons of Solothurn and Bern in Switzerland. We use data from a survey from 418 crop farmers (Späti et al., 2022). The data were collected using a split sample approach, investigating willingness to pay in one sample and willingness to accept in the other sample. We used a factor analysis to assign to each farmer from one sample a similar one from the second sample, thus obtaining an agent set with a specific willingness to pay and willingness to accept for each agent. This resulted in a set of 136 agents used for the simulation.

Variable rate technologies cover a whole range of technologies that can be used for site-specific nitrogen application. An important step in site-specific nitrogen fertilization is data collection. These data can be collected in a variety of ways, including soil sampling, satellite data, nitrogen sensors, or drone imagery, and vary in spatial resolution (Späti et al., 2021). In addition, the cost of the technologies are also different. For instance, satellite images are in some cases available for free or cost only a few francs, whereas nitrogen sensors cost up to several tens of thousands of francs if one wants to acquire the technology oneself.

## Methodology

We here use the agent-based modelling framework FARMIND (Huber et al., 2021). The purpose of this modelling approach is to simulate the adoption of precision agricultural technologies on Swiss farms. The model simulates the effect of different policy incentives on the adoption decision of variable rate technologies in wheat production considering heterogenous cognitive, social, and dispositional factors across individual farmers. Thereby, the model uses information on farmers' stated willingness to pay and willingness to accept from a choice experiment to simulate the effect of differently designed policy incentives (i.e., tax on nitrogen, subsidy per kg of reduced nitrogen, subsidy for a specific technology and area-based subsidy) on the adoption decision. The model also considers empirical data collected via surveys on farmers technology preferences, risk preferences and attitudes towards the environment in combination with the impact of policy measures on gross margins in wheat production. The emerging phenomena are a) the total amount of nitrogen reduced by the farm individual adoption of variable rate technologies and b) the change in total gross margins for the individual farm but also the whole farm community. Thus, the model allows to quantify the economic and environmental effect of the adoption of variable rate technologies in wheat production on Swiss farms.

For the calculation of the gross margins, which are then used for FARMIND, we use a bio-economic simulation model (Späti et al., 2021). Using this model, we are able to take into account varying spatial resolutions of different sensing approaches for site-specific nitrogen fertilisation, environmental heterogeneity at the field level, as well as market and policy conditions for calculating individual gross margins for each agent in the agent-based model.

To simulate farmers' decision-making, we focus on the farmers' individual perception of cost and benefits of variable rate technologies and link them to risk parameters, social orientation, and preferences for technologies. These aspects are combined in FARMIND using the so-called CONSUMAT framework, which links the different theoretical concepts into a structured sequence of modelling steps (Schaat et al., 2017). The parametrization of the model is based on the following empirical data (see Table 1): i) willingness to pay and willingness to adopt of variable rate technologies based on choice experimental data; ii) Risk preference parameters derived from farmers self-assessment of their risk behaviour; iii) Stated preferences for technologies and attitudes towards environment, and production; iii) Information on farmers social network (self-assessment); iv) census data to calculate farm individual benefits and costs from using variable rate technologies.

*Table 1. State variables and parameters*

| Category | State variable / parameters | Abbreviation | Source for initialization |
|---|---|---|---|
| (1) Farm and technology characteristics* | Adopted variable rate technology | $A$ | Späti et al., 2022 |
| | N application under the corresponding technology $A$ (kg) | $y_{At}$ | Based on simulation in Sub-model (Späti et al., 2021) |
| | Gross margin with adopted variable rate technology (1000 CHF) | $x_{At}$ | |
| | Wheat area in 2019 (ha per farm) | $area$ | Census data |
| (2) WTP /WTA | Farmer's perception of costs and benefits of variable rate technologies | $WTP_A$ / $WTA_A$ | Späti et al., 2022 |

| | | | |
|---|---|---|---|
| (3) Personal characteristics** | Risk preferences (risk averse, risk neutral, risk loving) based on cumulative prospect theory | λ, $\alpha^{+/-}$ $\phi^{+/-}$ | Späti et al., 2022 |
| | Tolerance level for activity dissimilarity to determine information seeking behavior | $d_i^{tol}$ | |
| | Preference for technology | $P_A$ | |
| | Reference gross margin to calculate satisfaction. | $V_i^{ref}$ | |
| (4) Social network | Number of peers a farmer is linked to (number of ties) | $n$ | Späti et al., 2022 |
| (5) Outcome variables | Prospect value | $V_i$ | Model endogenous |
| | Agents' activity dissimilarity | $d_i$ | |
| | Nitrogen use (in simulation run t) | $y_t$ | |
| | Gross margin (in simulation run t) | $x_t$ | |

FARMIND includes a two-tiered decision-making mechanism for managing farm resources. In a first step, agents choose a decision strategy. The model includes four behavioural strategies: repetition, optimization, imitation, and opt-out. In a second step, farm agents chose their actual pro-duction decision i.e., the adoption of variable rate technologies based on the options provided in the corresponding strategy. This two-tiered decision-making is implemented in three coding steps.

First, FARMIND calculates the distribution of gross margins over the farmers' memory length and the gross margins in the initialization year. On this basis, the model calculates the prospect value of the agent's gross margin considering the empirical based risk preferences. In addition, the model calculates the agents' dissimilarity to the other agents in the network with respect to technologies used in wheat production. Prospect value and dissimilarity are then used to calculate a strategy of each individual farmer i.e., repetition, imitation, optimization or opt-out (the latter would be equivalent to the status quo). We here use a farmer typology to parameterize the agents' individual characteristics. The typology is empirically derived from a farm survey that gathered information on farmers' personal characteristics (i.e., risk parameters, tolerance for being dissimilar to other farmers and environmental attitudes). This implies that each agent belongs to a certain farmer type with the same individual parameterization (for details see Section "Initialization of simulation"). Secondly, variable rate technologies are ranked according to the personal preferences of the farmer (also identified in the survey). A fuzzy logic algorithm identifies a sub-set of maximum two strictly preferred activities in the different strategies. Thirdly, based on the transferred choice sets, FARMIND chooses those technologies that maximize nitrogen reduction given a gross margin level (at least greater than the gross margin without adoption of variable rate technologies). The gross margins vary across scenarios (i.e., the type of policy implemented) and with the individual perception of costs and benefits of the corresponding technology derived from WTP and WTA estimates. The results from the adoption decision (gross margin and technology adoption) are then again transferred to the FARMIND strategic decision to update technology use and gross margin distribution of the agents.

For our analysis, we consider four different measures to support the adoption of site-specific nitrogen fertilisation. The first two measures relate directly to nitrogen and include a tax on nitrogen and a payment for each kilogram of nitrogen reduced. In the third measure, farmers receive a fixed payment if they adopt the technology. The fourth measure involves subsidising the area farmed with the technology.

**Results**

Table 2 shows the results for the N reduction target of 10% and results for the same policy measures under different field conditions. In the absence of supporting policy measures, a nitrogen reduction of 4% could be achieved. By applying a tax of 0.6 CHF per kg of nitrogen, a reduction of 10% is achieved. Likewise, this can be reached by a payment of 7 CHF per saved kg nitrogen, a lump sum payment of 2500 CHF for the application of the technology or a subsidy of 600 CHF per ha managed with the technology.

*Table 2: Results for the 10% nitrogen reduction target and for the same measures under changes in heterogeneity with respect to field conditions.*

| 10% reduction target | | | | | |
|---|---|---|---|---|---|
| Scenario | No Policy | Tax | N Payment | Technology Subsidy | Area Subsidy |
| Measure to achieve 10% reduction | - | 0.6 CHF increase of N price | 7 CHF payment per reduced kg N | 2500 CHF payment for tech adoption | 600 CHF per ha managed with technology |
| N Reduction [%] | 4% | 10% | 10% | 10% | 10% |
| CHF per reduced kg N | 0 | 4.35 | 5.95 | 26.15 | 37.10 |
| Reduced heterogeneity in soil type characteristics | | | | | |
| N Reduction [%] | 2.5% | 7% | 6% | 6.5% | 6% |
| CHF per reduced kg N | 0 | 5.05 | 6.30 | 39.35 | 52.45 |
| Reduced heterogeneity in soil types | | | | | |
| N Reduction [%] | 1.5% | 4% | 4% | 4.5% | 4.5% |
| CHF per reduced kg N | 0 | 5.60 | 6.20 | 33.40 | 51.85 |
| Change in the distribution of soil types (less patches) | | | | | |
| N Reduction [%] | 3% | 9% | 8% | 8.5% | 9% |
| CHF per reduced kg N | 0 | 5.65 | 7.90 | 24.75 | 33.25 |

Considering the efficiency of the respective policy measure, it seems that the two measures directly related to nitrogen use, such as taxation and payment for N reduction, are the most cost-efficient measures. Our first results indicate that the economic benefit, from the application of the technology and the associated reduction in nitrogen use highly depend on the underlying field heterogeneity. It seems that a reduction of heterogeneity in soil fertility conditions makes the policy measures less effective.

**Conclusion**

Understanding the factors influencing farmers' adoption decisions regarding sustainable technologies are key for designing effective policy interventions to support the adoption of such technologies towards more sustainable agriculture. With our analysis we aim to contribute to a better understanding of the factors that influence farmers' decisions to adopt more environmentally friendly technologies in small-scale farming systems and which policy measures can support the application of site-specific nitrogen fertilization. To this end, we combine an agent-based modelling framework FARMIND with empirical survey data and simulate the effects of different policy measures on adoption rates. Overall, we find that measures directly linked to nitrogen use, such as taxes on nitrogen or a payment for each kg of nitrogen reduced, are more cost-effective. Furthermore, the efficiency of the measures strongly depends on the heterogeneity of the field conditions.

The survey data show a very low actual adoption rate. Hence, this makes it difficult to validate the model (i.e., to compare it with observed adoption). In addition, there are uncertainties related to model parameterization based on survey data. Further sensitivity analyses need to provide insights into verification and conceptual validation of the simulation results. In addition, there could be a selection bias in the survey data, as farmers who are interested are more likely to have participated. Therefore, the results should be considered lower bounds.

Our results indicate that policy measures to support adoption of site-specific nitrogen fertilization should be directly related to nitrogen use. Moreover, the amounts of subsidies needed to achieve a 10% nitrogen reduction are relatively high, so it may be necessary to use other approaches, such as nudging, in addition to monetary measures.

Since social networks can also play a role in the diffusion of new technologies, this aspect could also be integrated into the analysis. Further research could thus explore the role of social networks in the adoption of precision agriculture technologies in smallholder systems. So far, we have not accounted for the observed heterogeneity in field conditions. Since this heterogeneity strongly influences the cost-effectiveness of the interventions, it would be very valuable to include empirical data on this aspect in the analysis. In addition, technology and price developments should also be considered in the analysis, as they might have an important effect on costs and benefits.

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