FARMIND
Farm Interaction and Decision Model

Model

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ODD + D protocol FARMIND

Overview

Purpose

The purpose of the model is to simulate agricultural production decisions. The model should reflect the heterogeneity in farmers decision-making processes based on standard and behavioral economic concepts. The key functionality of the model is to consider farmers' individual characteristics such as attitudes and risk preferences and the farmers' social network in the decision-making process. The model allows to inject diverse behavior into existing bio-economic simulation models and is intended to improve the understanding and explanation of farmer's decision-making trough hypothesis testing. Future applications of the model can be used to test and evaluate environmental impacts of farmers' production decisions e.g. under climate or policy changes.

State variables

Each agent represent an individual farmer. A farmer has (1) its personal characteristics (i.e., preferences, cognitive characteristics etc.) and (2) its social networks (i.e., family ties, producer organizations, knowledge networks etc.). The personal characteristics is defined by exogenous parameters for the underlying theoretical concepts i.e., cumulative prospect theory and adapted threshold values to identify CONSUMAT strategies (Table 2).

Personal characteristics		
Cumulative prospect theory	Loss aversion level	λ
	Valuation of gains	α^{+}
	Valuation of losses	α^{-}
	Probability weighting in gains	φ^{+}
	Probability weighting in losses	φ^{-}
	Prospect value	V_i
Threshold values to determine strategic heuristics	Reference income to determine perceived gains and losses and calculate satisfaction	V_i^{ref}
	Tolerance level for income change to determine information seeking behaviour	g_i^{tol}
	Tolerance level for activity dissimilarity to determine information seeking behaviour	d_i^{tol}
Farming preferences	Preference weight for agricultural activities	β_P
	Weight of personal experience	β_L
	Weight of social network	β_S
	Fuzzy size (number of considered activities)	S_F
Social networks		
	Number of peers a farmer is linked to (number of ties)	n
	Weight of ties (strength of linkage to peers)	β_n

Table 2: Characteristics of FARMIND agents for the calculation of strategic heuristics

In addition, FARMIND includes the following basic variables: number of farms i, year (or model run) t, farming activity A_i, income of farm i in year t i.e., x_{it}.

Each agent is linked to a bio-economic agricultural production model, which reflects the multi-output decision context of the farmer e.g., a farm level optimization model, or any other code simulates a constraint decision-making process in agriculture. This sub-model defines the spatial extent as well as the spatial and temporal resolution of the model.

Process overview and scheduling

FARMIND is based on a three-step modelling approach including a decision strategy (repetition, optimization, imitation, opt-out), the definition of preferred farming activities and an actual production decision i.e., the choice of an agricultural production activity (Figure 1).

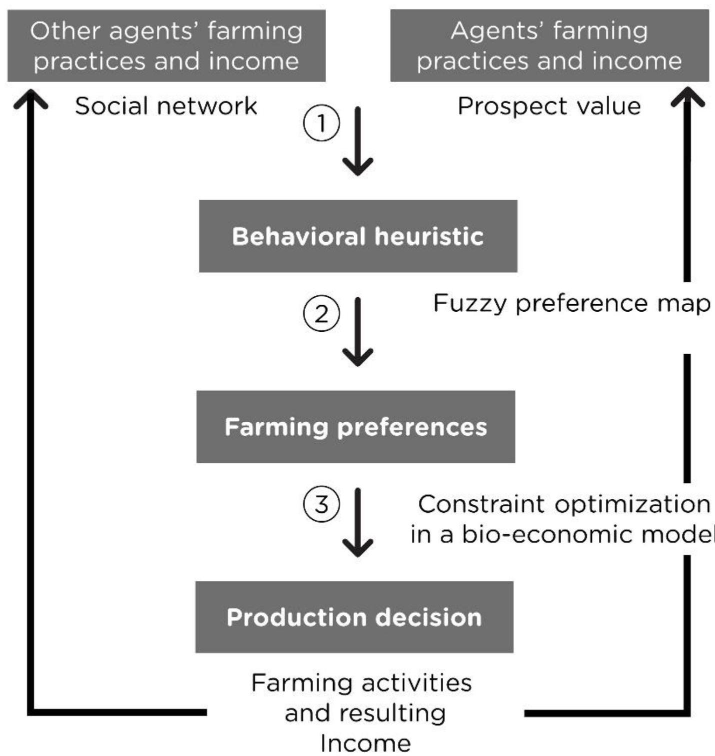

Figure 1: Flowchart of three step modelling approach in FARMIND

- *First step*: Based on the production activities in the past, FARMIND calculates the income distribution over the farmers' memory length and the income in the initialization year. On this basis, the satisfaction and insecurity levels of the agents are calculated to determine the strategic decision of each individual farmer (see individual decision making).

- *Second step*: Production activities are ranked according to the personal characteristics of the farmer. The fuzzy logic identifies a sub-set of strictly preferred activities for the imitation strategy. For the optimization strategy, the fuzzy size determines a maximum number of the ranked production activities. In the case of repetition, the choice sets is identical to the one in the previous year and for the opt-out strategy, farmers' receive additional non-agricultural activities (if applicable in the sub-model) or abandon the corresponding agricultural production.

- *Third step*: Based on the transferred choice sets, the sub-model then determines the production choices. The results from the production decision (income and activities) are then again transferred to the FARMIND strategic decision to update experience and income distribution of the agent.

Design concepts

Theoretical and empirical background

Despite their empirical importance, behavioral aspects are underrepresented in modelling farmers' decision-making in real-world setting. We here use a cumulative prospect theory and social network theory to build a generic agent-based model that allows to link farmer's complex decision-making with the strength of existing agricultural production models. The CONSUMAT framework links the different theoretical concepts into a structured sequence of modelling steps. In the current version, the model solely relies on theoretical assumptions and uses empirical findings from existing studies for parameterization. Future applications of the model have to rely on interview and/or survey data from individual farmers including different types of risk elicitation methods, e.g., lotteries and games with farmers.

Individual decision-making

Following the CONSUMAT approach, agents make decisions on their behavioral strategies according to their satisfaction and uncertainty levels. In FARMIND, an agent's satisfaction level in a year is reflected by the prospect value of incomes in year *t* and all previous years within the memory length. Income above (below) the agents' individual reference income are considered as gains (losses). For each income over the memory length, the prospect value is calculated using individual value and probability weighting functions. If the sum of these incomes is positive (negative), an agent is considered as satisfied (unsatisfied). Thus, the underlying risks and uncertainties in agricultural production are explicitly considered in the calculation of the agents' satisfaction. To calculate whether a farmer will engage in social processing or not, we calculate two different indices. Firstly, we calculate the percentage income change for year *t* and each farmer compared to the average income change over the memory length. We then compare this change between the individual farmer and all the agents in the model. If the difference between the individual change and the average change of income exceeds an individual tolerance level, the corresponding farmer engages in information seeking behavior. Thus, a wedge between the income growth of an agent and all the agents makes the farmer uncertain in the sense of the CONSUMAT. Secondly, we apply a dissimilarity index to represent the agents deviating behavior from other farmers.

<table>
<tr><td></td><td></td><td colspan="2">Satisfaction
Prospect value with reference income as threshold for the determination of gains and losses</td></tr>
<tr><td></td><td></td><td>> 0: satisfied</td><td>< 0: dissatisfied</td></tr>
<tr><td rowspan="2">Information seeking behaviour
Values for determining individual or social processing (threshold for income trend and activity dissimilarity)</td><td>< tolerance level: individual oriented</td><td>Repetition
The decision is represented by solving the sub-model without changes in available activities and technical coefficients of production.</td><td>Optimization
The sub-model has access to all activities restricted only by personal preferences based on the fuzzy preference map.</td></tr>
<tr><td>> tolerance level: social oriented</td><td>Imitation
The sub-model is extended with those activities that are used in the social network, restricted by personal preferences based on the fuzzy preference map.</td><td>Opt-out
The sub-model includes the opportunity to cease an activity, select non-agricultural activities or abandon production.</td></tr>
</table>

Table 2: Strategic decision and choice sets in FARMIND

We count the average number of activities performed in the agent network over the memory length. We then divide the average number for each activity that is performed by the agent and the network by all the activities performed in the corresponding network. The higher the value, the more similar an agent is to his peers. This index is compared to a tolerance level, representing the individual aptitude to consider deviating behavior of other farmers. A low tolerance level implies that the farmer is more likely to comply with social norms i.e., not being different from others. The combination of satisfaction and information seeking behavior defines the strategic choice of the farmer: repetition, optimization, imitation or opt-out (Table 2). Thus, agents adapt their strategies to changes in the environment (e.g. prices and yields in the sub-model) and the behavior of other farmers.

The sub-sets represent a bundle of farm activities (or production methods) that are in accordance with the farmers' personal and observed behavior. We apply the fuzzy out-ranking method to narrow down the options available in the sub-model. This method allows to distinguish preferences for production activities based on multiple criteria. In FARMIND, we apply three criteria to rank production activities:

- *Stated preferences for farming activities and/or production methods.* Stated preferences can be used to characterize individual values or believes, which advantage or exclude certain type of production activities (e.g. dairy) or production methods (e.g. organic). The higher the preference, the more likely the corresponding activity appears on the top of the fuzzy ranking.

- *Revealed preferences of farmers' observed behavior in the past.* If a farmer continuously choose a certain activity, we can assume that this is in accordance with his own preference and thus is more likely to be at a higher position in the fuzzy ranking. In addition, repetition represents an individual learning process (or professionalization) if the farmer keeps doing the same thing which also increases the probability of that activity being in the choice set.

- *Farmers' observation of the behavior of his peers.* In the case in which an agent chooses to imitate, activities that can be observed in the agents' network are ranked above other activities. In addition, the experience of the peers with the corresponding production activities is also considered as a factor that affects the relative ranking of production activities. If a certain activity is chosen within one network over time, the social "transaction costs" to implement this behavior reduces and thus increases the probability that additional activities appear in the farmers' output space.

We normalize the underlying values using the maximum value for each criteria and predefine a lower and an upper indifference threshold. If the difference of the normalized values between activity A_1 (with a higher value) and A_2 (with a lower value) is smaller than the lower threshold these activities are considered as being indifferent i.e., the agent has no preference for one of the two activities. If the difference is greater than the upper threshold, A_1 is strictly preferred over A_2. If the difference between the two activities falls within the interval of the lower and upper threshold, A_1 is weakly preferred over A_2. In addition, we add exogenous weights to the three different criteria, which allows to characterize preferences for each agent individually. Based on the ranking i.e., a list of production activities, we implemented two different algorithm to determine the final choice set for the four strategies. FARMIND can be applied using a non-dominance score that endogenously defines a small sub-set of activities that are always strictly preferred over the rest of the production activities. However, non-dominance score might reduce the flexibility of the model too much. Thus, FARMIND includes also an exogenous parameter that allows to define the size of the production activities that should be considered in the imitation and optimization strategy respectively. The reduced choice set is then passed to the sub-model.

Learning

Agents have a memory of their production activities. The length of memory is determined exogenously and can be set individually for each agent. The more experience an agent has with respect to a production activity, the higher its weight in the fuzzy preference ranking. More experience also increases the weight of a specific production activity in the agents' social network. Thus, agents learn that behavior from peers that are performed within their social network over a longer time horizon. Thereby, the weight of experience, the learning rate, is represented as a logarithmic function that converges to one over the period of the memory length. This mechanism of learning from peers increases the probability of adaption and diffusion of a production activity when more agents perform this activity over a longer time horizon.

Sensing

Agents can correctly observe the activities their peers perform and memorize the production activities in the past. They can also observe its' own and the average income of the whole population. Agents memorize this information for periods of their memory length. Assumptions about prices, yields or other information with respect to the production decision are condensed in the realized income. In principle, agents do not have costs for gathering information. However, the learning rate slows the information exchange between agents in the social network and thus information from the peers is not directly and in every time step available for the individual agent.

Individual prediction

Agents change their decision strategy based on their individual prospect value. Using their realized income in the past and the individual value and probability weighting functions, agents “predict” the value of their realized income according to the cumulative prospect theory.

Interaction

Agent observe the behavior of their peers in the case they choose to imitate. Other interactions e.g. on (land) markets or with environmental entities critically depend on the sub-model and thus are exogenous to FARMIND.

Collectives

The social network allows to predefine a static collective that is more likely to adapt production activities from each other. There is, however, no dynamic mechanism from which collectives emerge.

Heterogeneity

Agents can differ with respect to all parameters presented in Table 1. This heterogeneity leads to different decision strategies for the individual agent i.e., repetition, optimization, imitation, opt-out. In addition, the underlying sub-model also allows to differentiate the agents e.g. according to their production resources (labor, capital, land) or with respect to their environmental production conditions.

Stochasticity

There are no randomized variables or parameters in the calculation of satisfaction, information seeking behavior and the choice sets. A full calibration of all the parameters in FARMIND, however, may be unattainable in individual applications of the model. Thus, random initialization processes may be indispensable for specific applications. We here used randomization for the generation of the social network, the distribution of preferences for production activities, agents’ reference income and tolerance levels as well as the parameters used to calculate the prospect value (see initialization).

Observation

The model output of FARMIND are choice sets of agricultural production activities that are passed to an optimization model. The realized income and the actual production activities chosen by the agent is then transferred back to FARMIND. The emergent phenomena in FARMIND are heterogeneous decision strategies that result in different production outcomes in the sub-model.

Details

Implementation

FARMIND is written in Java. The model is available on Github: https://github.com/AECP-ETHZ/FARMIND. Code for the initialization and sensitivity analysis are written in R. The applied sub-model in this contribution is written in GAMS and uses a CPLEX solver. The applied sub-model in this contribution is available from here: https://doi.org/10.3929/ethz-b-000184083

Input data and initialization

FARMIND uses five input data sets: i) a social network including ties and weight of ties between agents; ii) a matrix of each agents' preferences for the production activities available in the sub-model; iii) a table of the agents' individual characteristics (cf. Table 1); iv) a list of production activities the agent performed in the past; and v) a list of initial incomes i.e., realized incomes from the performed activities over memory length. In the here presented results, the first three input files are generated by a random process and the impact of randomization is tested in the sensitivity analysis. For the initialization of activities and incomes in the sensitivity analysis, we distribute randomly the available activities to the model agents so that the share of the different weed control strategies complied with the most frequent scenario in Böcker et al. (2018). For the initialization of initial incomes in our application, we run the model over five years with repeating agent. For future applications, the initialization has to be adapted to the functionality of the sub-model and thus should vary depending on model purpose and research question.

Sub-model

FARMIND needs a sub-model that provides the effective decision of a farmer in a (constraint) optimization process. In principle, any model that simulates the individual choice between different agricultural activities based on an economic criterion e.g., yearly revenues, gross margins or incomes is suitable as sub-model. There exist a broad set of bio-economic and farm models that fulfill these criteria (for reviews see Janssen and van Ittersum, 2007; van Wijk, Rufino et al., 2012; Shrestha, Barnes et al., 2016; Reidsma, Janssen et al., 2018). Moreover, the implementation of our framework would also allow to integrate FARMIND, i.e., the CONSUMAT strategies in other ABM approaches using mathematical programming models as agents such as MP-MAS (Schreinemachers and Berger, 2011) or AgriPoliS (Happe, Kellermann et al., 2006).

To demonstrate a "proof of concept" of our modelling framework, we used the bio-economic weed control model for silage maize production developed by Böcker et al. (2018) as sub-model in an global sensitivity analysis (see Appendix B). The model had been applied to assess the economic impact of a Glyphosate ban on maize production (Böcker, Britz et al., 2018; Böcker, Britz et al., 2019). It is able to identify economically optimal herbicide strategies in silage maize under given pesticide and crop prices as well as specifications and regulations of pesticide use. The model is calibrated with detailed data on weed abundance, yield losses and herbicide efficacy of 377 municipalities in the federal state of North-Rhine-Westphalia (Germany). The optimization model is based on two steps. Firstly, maize yield is estimated using a damage control approach.

This approach determines the effect of herbicides (a damage control input) on weeds (damaging organism) and then calculates the yield reduction from surviving weeds. The model considers the 32 most important weeds in the region over a period of 13 years and assesses the effect of 19 pre- and 55 post-sowing strategies including all herbicides recommended by the Chamber of Agriculture in North-Rhine-Westphalia. Estimated yield depends on weed pressure i.e., the time of maize emergence in relation to weed emergence, and the attainable yield based on soil and climatic conditions. The model also estimates the yield response to mechanical weed control. The resulting yield function has an exponential form, implying decreasing marginal weed control when increasing herbicide input or mechanic control. Based on the yield estimation over time and space, net profits for each weed control strategy are calculated accounting for maize prices and input costs, which are also dependent on weed pressure. Secondly, the model chooses the optimal pre- and post-sowing weed control strategies maximizing net profits. In Böcker et al. (2018) it is assumed that farmers know weed pressure and realized yield and the corresponding decision on the weed control option is deterministic under the restriction of a two-year cropping period which is a standard farming practice. In Böcker et al. (2019), this approach had been expanded to account for uncertainty in these parameters using a stochastic production function and risk preferences of farmers. Results of the model show that a glyphosate ban would cause a shift towards more mechanical weed control measures, but economic impacts would be small (Böcker et al. 2019).

To link the weed control model to FARMIND, we used the deterministic version presented in Böcker et al. (2018). This original model was designed for a two-year cropping period. To simplify the exchange between FARMIND and the sub-model, we here consider only yearly decisions and equate municipalities with agents equipped with random preferences on weed control activities, random decision characteristics i.e., cumulative prospect as well as reference income and tolerance levels and random social networks. To account for uncertainty, we model the choice of weed control strategy in two steps varying maize prices. First, it calculates the expected gross margin for all the activities in the choice set using the average maize price over the memory length (t-1 – t-5). The agent then chooses the corresponding production activity. Secondly, the income of the resulting production activity is calculated with the updated price and yield information of year t. Exogenous parameter in the bio-economic weed control model that determined yields (attainable yields, time of weed emergence etc.) are kept constant in the sensitivity analysis. To assess the impact of the different decision strategies on weed control, we here summarize the weed control options into three categories: weed control with Glyphosate, weed control without Glyphosate but other herbicides and pure mechanic weed control. For the presentation of the effect of different behavior on productions activities, we run exemplary scenarios with changes in maize prices. The sub-model determines the weed control options in two steps.

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