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Bridging behavioural factors and standard bio-economic modelling in an agent-based modelling framework

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Abstract

Agent-based models are important tools for simulating farmers' behaviour in response to changing environmental, economic or institutional conditions and policies. This article introduces an agent-based modelling approach that combines behavioural factors with standard bio-economic modelling of agricultural production. More specifically, our framework integrates the cumulative prospect theory and social interactions with constrained optimisation decisions in agricultural production. We apply our modelling approach to an exemplary bio-economic model on the assessment of weed control decisions. Results show the effects of heterogeneous farm decision-making and social networks on mechanical weed control and herbicide use. This framework provides a generic and conceptually sound approach to improve the scope for representing farmers' decision-making and allows the simulation of their decisions and recent advances in behavioural economics to be aligned with existing bio-economic models of agricultural systems.

KEYWORDS

agent-based model, bio-economic modelling, farmer behaviour, simulation, weed control

JEL CLASSIFICATION

C61; C63; Q12; Q15

1 | INTRODUCTION

Farmers' behaviour is complex and must be recognised as a key factor when assessing policy, technology or environmental changes in agricultural systems (Grêt-Regamey et al., 2019). Despite an increasing number of agricultural systems models (Jones et al., 2017), the representation of farmers' decision-making in linked socioeconomic and biophysical models is still a major challenge (Malek et al., 2019; Reidsma et al., 2018). In this context, agent-based models (ABMs) have become an important simulation tool for modelling farmers' behaviour (An, 2012). They represent a process-based 'bottom-up' approach capable of simulating emergent phenomena such as farm structures or the provision of ecosystem services. The main advantage of ABMs is that they permit the inclusion of the cognitive, emotional, personal and social processes that underlie human behaviour when modelling farmers' decision-making. There is increasing evidence that these behavioural factors are of great interest, both from a scientific and policy point of view, and must be considered when modelling the consequences of farmers' decision-making (e.g. Brown et al., 2020; Dessart, et al., 2019).

We propose a novel generic modelling approach to incorporate farmers' heterogeneous decision-making and underlying behavioural factors into existing agricultural production models or ABMs. Our modular modelling framework conceptually links decision-making under risk with social comparison processes and the representation of bounded rationality in constraint simulation approaches. This forms a bridge between agricultural agent-based modelling of farming systems, cutting-edge behavioural economics and social network research. We illustrate our modelling approach using an assessment of weed control decisions in German silage maize production.

The pioneering work of Balmann (1997) and Berger (2001) laid the foundation for agricultural ABMs (for reviews see e.g., Berger & Troost, 2014; Brown et al., 2017; Filatova et al., 2013; Nolan et al., 2009). Their work was also the basis for further generic and modular modelling approaches that have emerged in recent years (Magliocca et al., 2015; Murray-Rust, Robinson et al., 2014). These models represent manifold heterogeneous decision-making, including bounded rationality—that is, the concept that farmers have limited cognitive capacities or resources when making decisions (Groeneveld et al., 2017; Schill et al., 2019; Schlüter et al., 2017). However, models mostly focus on income maximisation or the expected utility theory in their representation of decision-making (Huber et al., 2018). Moreover, the integration of recent advances in behavioural economic research for policy analysis (e.g., Colen et al., 2016; Thoyer & Préget, 2019) into ABMs has not yet been exploited. This means that although theories and concepts like the cumulative prospect theory and socially oriented behaviour that are fundamental aspects of farmers' decision-making under risk, they are currently inadequately incorporated into agricultural systems modelling. More recently, ABMs emerged explicitly combining uncertainty aspects and social interactions in agricultural systems (Huber et al., 2018). For example, studies specifically address questions of disease control in crops and animal husbandry (e.g., Pacilly et al., 2019; Sok & Fischer, 2019) as well as farmers' pesticide use (Grovermann et al., 2017). However, these models are usually case study specific (Huber et al., 2018). Thus, it is still an open question just how behavioural economic research can be aligned with standard bio-economic modelling approaches to assess policy, technology or environmental changes in agricultural systems more comprehensively.

We develop an agent-based modelling approach FARMIND (FARM Interaction and Decision-making) to address this question by adding three contributions to the literature. First, the generic and modular framework FARMIND establishes a coherent and transferable link between a heterogeneous representation of decision-making and a detailed appraisal of farming activities. This allows behavioural factors and heterogeneous decision-making to be incorporated into the simulation of crucial emerging phenomena in agricultural systems, such as ecosystem service provision or environmental pollution due to individual decisions or interactions. The key modelling feature is that FARMIND can be linked to numerous potential bio-economic simulation models in a three-step modelling approach. Secondly, FARMIND allows for the fact that the role played by uncertainty in farmers' decision-making differs across individual farmers and is thus subjective by nature. Therefore, our framework forms a bridge to recent empirical applications of farmers' behaviour based on the cumulative prospect theory. This is currently lacking in most ABMs. Thirdly, FARMIND provides an endogenous representation of socially oriented behaviour in social networks allowing for varied strategic behaviour *within* a simulation run (e.g., Jager et al., 2000).

The article continues with our presentation of the conceptual background of FARMIND and a description of the conceptual alignment of complex human behaviour subject to the cumulative prospect theory, social networks, and farming preferences with the strength of agricultural programming models and their detailed overview of farming activities. We then present an existing bio-economic modelling approach that simulates weed control decisions with special focus on herbicide use. This weed control model is integrated as a sub-module of FARMIND and then used to illustrate the formalisation of farmers' decision-making in FARMIND. It also serves as a 'proof of concept' demonstrating that the implementation of the framework leads to a meaningful diversification of farmers' decisions depending on behavioural factors. Finally, we discuss our approach with respect to its functionality, model uncertainty and further challenges and conclude with upcoming developments and applications of the framework.

2 | CONCEPTUAL MODEL FRAMEWORK

A large number of agricultural bio-economic models and ABMs focus on rational decision-makers and maximisation of profits as the underlying theoretical concept (Brown et al., 2017; Huber et al., 2018; Kremmydas et al., 2018). These models integrate information about farm structures, environmental variables, price and market developments and policy instruments. Extensive empirical evidence indicates, however, that in reality farmers do not base their production decisions solely on income maximisation (e.g., Dessart et al., 2019; Howley, 2015; Howley et al., 2017; Malek et al., 2019). Based on this research, our conceptual framework focuses on three extensions of the assumption that farmers are profit maximisers by including prospect value, social networks, and farming preferences in the simulation of famers' decision-making (Figure 1a). In the following, we explain the importance of these three concepts for our modelling purpose, that is, to align behavioural factors with programming models of agricultural systems.

First, decision-making under risk and uncertainty is a crucial issue as farmers often face a number of environmental, market and political risks concurrently. It follows that risk perception and preferences are important concepts in agricultural economics (e.g., Chavas, 2004). In particular, their conceptualisation in the framework of the cumulative prospect theory (Kahnemann, 2003) has proved useful when seeking to explain farmers' behaviour (e.g. Bontemps et al., 2020). Empirical evidence indicates that farmers' behaviour is influenced by their risk aversion and subjective probability weighting (e.g. Bougherara et al., 2017; Cerroni, 2020; Holden & Quiggin, 2017; Iyer et al., 2020). Moreover, our framework allows us to acknowledge that farmers' risk preferences are context-dependent (Reynaud & Couture, 2012) and that loss-aversion is strongly influenced by the choice of the reference point (e.g. Streletskaya et al., 2020).

Secondly, people often rely on the opinions and observed behaviour of their peers, especially when facing decisions with uncertain outcomes (Skevas et al., 2021). The use of the social network theory allows important feedback mechanisms to be integrated into farmers' decision-making, thus taking advantage of process-based adaptation and diffusion mechanisms (Brown

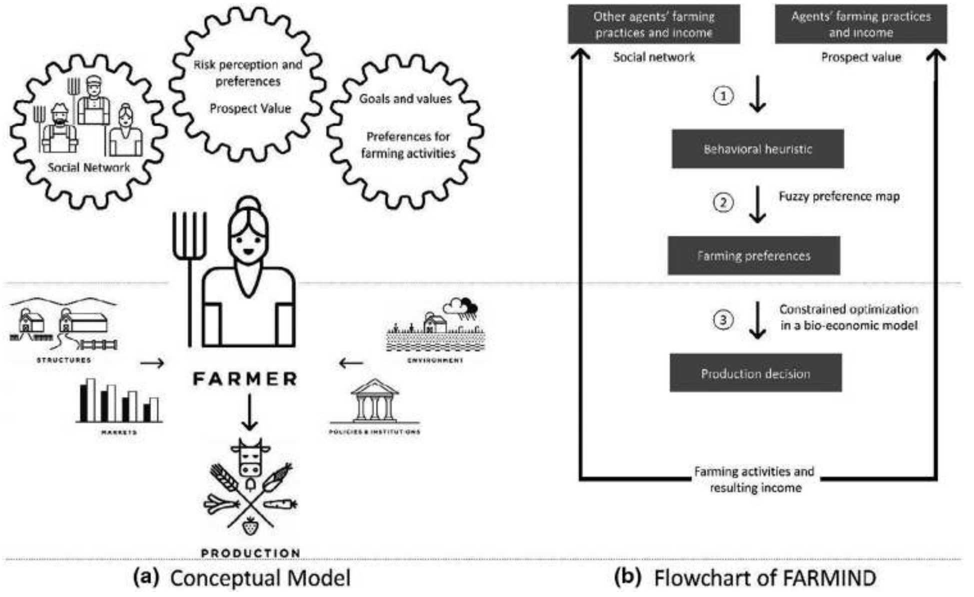

FIGURE 1 (a) Conceptual framework of FARMIND including prospect value, social networks and farming preferences. (b) Flowchart of FARMIND including three steps: (1) the agent makes a strategic decision based on four heuristics based on prospect value and their social network; (2) the agent's decision space is reduced to activities preferred by the agent using fuzzy preference maps; and (3) the agent makes a production decision in a sub-model resulting in the choice of farming activities and the corresponding income. This information serves as a basis for the agents' strategic decision in the next model iteration

et al., 2016; Schreinemachers et al., 2009; Schreinemachers et al., 2010). Existing research shows that farmers' decisions are often influenced by social networks, for example, when learning and acquiring different types of knowledge and information about agricultural technologies or practices on both individual and cooperative levels (most recently: Bell et al., 2016; Cai & Xiong, 2017; Latynskiy & Berger, 2017; Manson et al., 2016; Rasch et al., 2016).

Thirdly, there is empirical evidence that goals and values—such as social, lifestyle or family objectives—also play a role in farmers' decision-making (Brown et al., 2020; Howley, 2015; Howley et al., 2014). In this context, farmer's life satisfaction is not necessarily directly associated with his/her actual business success (Howley et al., 2017) and it is possible that a farmer might view his/her profession as a vocation that has a value in itself (e.g., Willock et al., 1999). Existing research often applies typologies to these behavioural components in simulation studies ranging from a local (e.g., Grêt-Regamey et al., 2019) to the global scale (Malek & Verburg, 2020).

Based on this theoretical and conceptual background, FARMIND uses a three-step modelling approach to align behavioural factors with standard bio-economic modelling (Figure 1b).

In a first step, agents in FARMIND make a heuristic decision defining the strategy to be adopted. These decisions are derived from the generic ABM framework CONSUMAT (Jager, 2017; Jager & Janssen, 2012) that identifies four different strategies: repetition, optimisation, imitation and inquiry. Each agent's choice of strategy is influenced by social networks and risk preferences. In a second step, FARMIND uses the concept of fuzzy preference maps to reflect agents' dispositions, such as preferences for certain farming activities or resistance to change in the corresponding decision context. Fuzzy preference maps allow farming activities to be ranked according to the agents' preferences and tailored to meet the strategic heuristic chosen in the first step. These first two steps are calculated in our generic modelling approach. In a third step, the actual production decision, that is, the choice of farming activities, is then simulated using a sub-model applying constrained optimisation in a bio-economic model approach.

In the following, we describe the role and implementation of these three steps in greater detail. The bio-economic model and the formalisation of the model are presented in the next sections.

2.1 | Strategic heuristics

The strategic heuristics implied by the CONSUMAT—that is, repetition, optimisation, imitation and inquiry—have been used to model farmers' production decisions in several agent-based modelling approaches (most recently: Pacilly et al., 2019; Van Oel et al., 2018). These heuristics stem from two underlying variables: uncertainty and satisfaction. Uncertainty determines the farmers' information seeking behaviour, that is, whether they will personally seek more information or compare their own behaviour to that of both agents in their social network and other farmers in general. Satisfaction determines the extent to which farmers are motivated to invest effort in improving their situation. The combination of these two variables leads to four different types of strategic heuristics (cf. Table 1).

If farmers are satisfied and do not feel uncertain, they will abide by a production decision. A satisfied farmer who feels uncertain will search for additional information and start imitating the behaviour observed in their social network. Those who feel certain but are dissatisfied will strive to optimise their situation. Finally, the combination of dissatisfaction and insecurity leads to an examination of the behaviour adopted by other agents in general (inquiring). When simulating farmers' decision-making, inquiring may also include seeking activities outside the agricultural sector. Off-farm diversification is a relevant option for many farm households in Europe (e.g., Weltin et al., 2017). However, bio-economic models of agricultural systems rarely include off-farm income opportunities. Thus, depending on the sub-model used for the constrained optimisation, we define the inquiring strategy as a step towards giving up a specific

TABLE 1 Strategic decision and choice sets in FARMIND

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

farming activity, going in for part-time farming or even to leaving the agricultural sector (opt-out strategy).

These strategic heuristics are linked to the cumulative prospect theory and corresponding findings from recent economics experiments in the agricultural sector. Satisfaction and information-seeking behaviour is defined as follows:

- *Satisfaction*: The prospect value of a farmer's income serves to represent their satisfaction level. Thus, we assume that satisfaction is not merely the outcome of current behaviour, but also includes the prospect value of future (uncertain) income based on the farmer's experience and cognitive biases. A farmer is satisfied if the prospect value over a defined period exceeds zero, that is, gains are at least as high as losses. We use a reference income as the threshold value to determine gains and losses for each agent.
- *Information seeking behaviour*: We use two different values to determine whether an agent in our ABM will use an individual or a socially oriented decision heuristic. The first value indicates the similarities or differences between the agent's farming activities and those of their peers. This dissimilarity index represents the behavioural deviation compared to other farmers. Thus, a farmer who observes a change in the farming activities of others in their network becomes increasing likely to adopt information seeking behaviour (for a similar application see e.g., Van Oel et al., 2018). This reflects the concept that farmers learn from comparing themselves with others in their network who are endowed with similar characteristics and capabilities (see e.g., Läpple & Kelley, 2015). The underlying conceptual mechanism assumes that a farmer will try to imitate those agents who have similar production characteristics because imitation helps keep the costs of cognitive efforts down and minimises risks of failures when trying to change production (e.g., Jager & Janssen, 2012; Le et al., 2012).

The second value focuses on differences in economic performance. The underlying mechanism assumes that if an agent in FARMIND recognises that their income is not developing on a par with others in their network, they will engage in social processing, such as imitation or inquiry (e.g. Morgan & Daigneault, 2015). This applies especially when a crisis or shock triggers new behaviour patterns (e.g., Sutherland et al., 2012; Zilberman et al., 2012). Consequently, a farmer will engage in social comparison if their own income lags behind the income level of their peers. We focus on the idea that farmers will compare themselves to those who outperform them (see e.g., Polhill et al., 2001). This adds an important functionality to the model: information seeking behaviour is not triggered by structural characteristics alone (e.g., farming activities), but is also influenced by changes in relative income due to price or yield changes connected with these production activities. The resulting model endogenous representation of behavioural heuristics also considers the decisions of other farmers within a social network.

Each agent has a tolerance level for changes in income growth and activity dissimilarity. This is the basis for the threshold levels which determine individual or social processing in the model, just like the reference income in the calculation of satisfaction.

2.2 | Preferences for farming activities

Farmers' decision-making is often driven by dispositional factors, such as reluctance to change or personal preferences for certain activities (Brown et al., 2020; Dessart et al., 2019). In many ABM approaches, farm typologies represent personal preferences for farm activities or production methods. However, the type of decision-making often remains static because agents have clear-cut preferences for certain farm activities, whereby many real-world decisions are based on relatively imprecise or fuzzy preferences (e.g., Bellman & Zadeh, 1970). In this case, fuzzy implies that there are not only distinct preference relations, but also weak preferences or indifference between alternatives (Dubois & Perny, 2016). Fuzzy outranking methods are a tool that accounts for different preferences when simulating agents' decision-making. These methods allow the aggregation of different types of preference information. An algorithm ranks preference scores for different farming activities into pairs that reveal a distinct preference—that is, an activity is always preferred over another—and into pairs viewed with indifference—that is, the farmer does not exhibit a clear preference for either. Based on this comparison, the method can rank farming activities according to the agents' preferences. Finally, the so-called non-domination score (see Orlovsky, 1993) allows the endogenous determination of a subset of the best alternatives available to the farmer. These subsets represent a bundle of farming activities that conform with the farmers' personal preferences.

2.3 | Production decision

Bounded rationality means that farmers have limited resources at their disposal when making decisions. Therefore, the agents in FARMIND choose a strategic heuristic to economise cognitive efforts (Le et al., 2012). However, given the boundaries of the heuristic, agents make rational decisions whereby they choose those farm activities that promise the largest income based on their biophysical, technological and economic constraints, that is, they make the most of their limited resources (Buysse et al., 2007). Mathematical programming models reflect complex interlinkages between different production options and farm resources (Troost & Berger, 2015). There is a wealth of mathematical programming models applied to agriculture (see reviews by, e.g., Reidsma et al., 2018; Shrestha et al., 2016). In the most prominent European agent-based approaches such as MP-MAS or AgriPoliS, farm level models represent a mixed integer programming problem for production and investment activities (see e.g., Huber et al., 2018 for an overview). The underlying concept in FARMIND is that farmers focus on economic maximisation based on their biophysical and economic constraints when taking their production decisions, and they include objectives influencing long-term performance and indicators associated with sustainability in their strategic decision-making (see also Mandryk et al., 2014). The advantage of this third step is that, basically, any bio-economic modelling approach can be used in our third modelling step as long as it provides a calculation of farming activities and the corresponding income. Thus, it paves the way for a modular development of ABM in agriculture (Bell et al., 2015).

In the next section, we introduce the decision context and the bio-economic modelling approach used here for a 'proof of concept'. This allows us to combine the formalisation of the modelling steps (in the following section) with concrete examples of how FARMIND works.

3 | BIO-ECONOMIC MODELLING OF WEED CONTROL IN MAIZE

Based on our conceptual approach, FARMIND requires a sub-model that provides a farmer's effective decision in a (constrained) optimisation process. In principle, any model that simulates the individual choice between different agricultural activities based on an economic criterion—for example, yearly revenues, gross margins or incomes—is suitable as a sub-model.

We use the bio-economic weed control model for silage maize production developed by Böcker et al., (2018, 2020) to serve as a 'proof of concept' for our modelling framework. The model was applied to assess the economic and environmental impact of a glyphosate used in maize production in 377 municipalities in Germany. The increase of glyphosate in weed control is a highly contested issue and raised environmental and health concerns in agricultural systems worldwide (Clapp, 2021). Thus, the question of pest management and policy interventions in this field are currently the subject of ongoing debates (e.g. Möhring, Ingold et al., 2020). There is ample evidence that risk perception and preferences influence farmers' pest management decisions (Pacilly et al., 2019; Möhring, Wuepper et al., 2020) in addition to important knowledge spill-overs from other farmers and actors (Grovermann et al., 2017; Wuepper et al., 2020). The model used here can identify economically optimal herbicide strategies in silage maize production under given input and output prices, specifications and policy or industrial regulations for pesticide use—for example, whether the use of glyphosate is allowed (Figure 2).

This simulation of weed control decisions is linked to the strategic heuristics that potentially affect the decision beyond the underlying bio-economic processes. Thus, a farmer's decision is affected by risk preferences, social network and preferences for certain farming activities, that is, weed control options. Recent research shows that these factors are important in the context of pesticide use decisions. For example, a farmer might deviate from purely income maximizing strategies: (a) to stick to certain behaviour regardless of the information available (e.g. Möhring, Wuepper et al., 2020) or policy conditions (Giannoccaro & Berbel, 2013), b) because he/she is guided by risk behaviour (Böcker, Britz et al., 2020; Möhring, Bozzola et al., 2020); or c) because he/she is influenced by their social network (Bakker et al., 2021; Wuepper et al., 2020).

In the weed control model, agents choose a combination of pre-sowing and post-sowing weed control options. The effect of the different control options on the attainable yield is quantified using a damage control function approach. This approach implies that the farmers' choice of the pre- and post-sowing control mechanisms will affect the population of the damaging

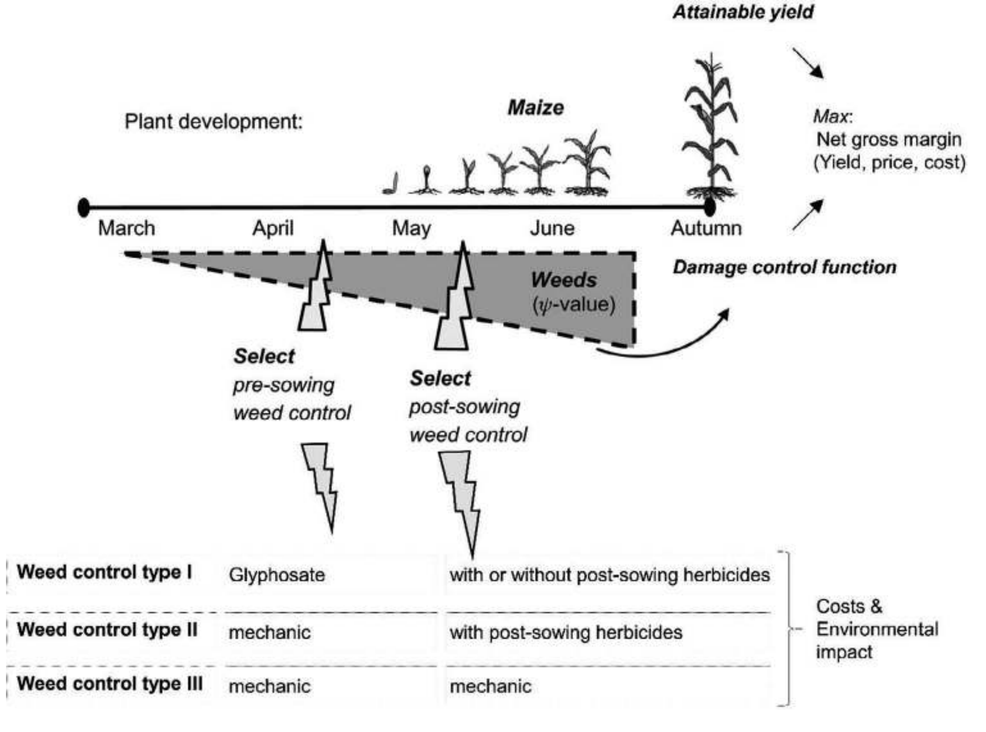

FIGURE 2 Modelling weed control types in maize production as a sub-model in FARMIND. Note: Weed control strategies can be categorised into three main types: (i) options including glyphosate as pre-sowing weed control, (ii) options without glyphosate but the use of other post-sowing herbicides, and (iii) mechanical control only. Source: Adapted from Böcker et al., (2020)

organism (i.e., weed) and that the surviving weeds determine the reduction in the attainable yield. The agent maximises the gross margin resulting from the effective yield depending on attainable yield and weed emergence (Ψ-value in Figure 2) as well as maize price and the costs of the weed control option. More specifically, farmers maximise expected gross margin $E(\pi)$ in year t for different pre- (index b) and post-sowing (index h) weed control strategies defined as:

$$E\left(\pi_{m,t,b,h}\right) = \left[y^{*}_{m,t,b,h} \cdot E\left(p\right) - c_b\left(b_i\right) - c_s\left(b_i\right) - c_h\left(h_i\right) - c_f\left(y\right) - c_o\right] \quad (1)$$

where $y^{*}_{m,t,b,h}$ is the expected yield, $E\left(p\right)$ is the expected price for maize, $c_b\left(b_i\right)$ and $c_h\left(h_i\right)$ are the pre-sowing (including tillage) and post-sowing weed management costs for a plant protection strategy, $c_s\left(b_i\right)$ are variable costs for sowing depending on the pre-sowing strategy, $c_f\left(y\right)$ are costs for fertiliser depending on the yield and c_o are other costs.

The bio-economic weed control model is calibrated with detailed data on weed abundance, yield losses and herbicide efficacy from the case study region of North-Rhine-Westphalia (Germany). Maize yields depend on spatially explicit weed pressure (based on NetPhyD & BfN, 2013) and attainable yield, for example based on soil and climatic conditions. The model calculates the effects of the 32 most important weeds (based on de Mol et al., 2015) on the attainable maize yield on the level of 377 municipalities (which also represents the number of agents in our application). Weed occurrence and weed pressure, as well as attainable yields, are site specific and the chosen weed control options determine the actual loss of yields due to weed pressure.

The farmers can choose between 19 pre- and 55 post-sowing strategies including mechanical weed control, all relevant herbicides and combinations thereof. Each strategy has a specific effect on weed abundance. The costs for weed control are also strategy specific. Consequently, weed control choice affects the effective maize yield and gross margins.[1] The model itself is deterministic in that it selects only the best weed control strategy over a two-year cropping period, which is a standard farming practice in this region. Model outputs show the gross margin maximising weed control strategy for different times of maize emergence compared to weeds and different price scenarios. Based on this output, pesticide load indicators and energy consumption can be calculated to assess potential adverse effects of herbicide use on the environment (Böcker et al., 2020).

We use these outputs—that is, the yearly gross margin and the choice of weed control options—to combine the bio-economic model of weed control with the conceptual framework of FARMIND and calculate the strategic heuristic in the next model iteration, in this case the year (see Figure 1). A model run ends with the agents' annual decision on weed control. The strategic heuristic for the following year is chosen based on the gross margin and the decisions of the other farmers in the social network. We classify the different weed control options (i.e., 19 pre- and 55 post-sowing, total $n = 72$) into three main types to assess the impact of the different decision strategies on weed control: (i) options that include glyphosate as pre-sowing weed control; (ii) options without glyphosate as pre-sowing weed control, but still enable the use of other herbicides for post-sowing weed control; and (iiii) no chemical weed control in both pre- and post-sowing phases, that is, using mechanical weed control strategies.

[1]All data and codes are available in Böcker et al. (2018), 'Bio-economic model on weed control in maize production (Version II)', https://doi.org/10.3929/ethz-b-000300439.

4 | MODEL IMPLEMENTATION

In this section, we present the basic calculations defining the strategic heuristics in FARMIND and add an example of how our generic framework can be understood in the context of farmers' weed control decisions. We then show how our framework accounts for preferences in farming activities. Model code and description are publicly available.[2] In addition, the model is also described using the ODD+D protocol (describing human decisions in ABMs), a standard protocol in agent-based modelling (Appendix SA).

We calculate satisfaction and whether a farmer adopts information seeking behaviour or not to identify the choice of the strategic heuristic, that is, whether a farmer intends to continue with the same type of activities or adopt an optimisation, imitation or opt-out strategy. Each farmer i has a set of personal characteristics used in the calculation (Table 2). These characteristics are translated into model parameters describing: (i) the cumulative prospect theory; (ii) threshold values for determining strategic heuristics; (iii) social network characteristics.

4.1 | Satisfaction

A farmer's satisfaction level is measured as the prospect value of their past incomes x_t over a predefined period of years t, which is termed as memory length m in FARMIND. By definition, prospect value is calculated using a value function and decision weights. Assuming that a set of past incomes of farm i in year t are $\left\{x_1, \cdots, x_m\right\}$, and value function and decision weight are $v\left(x_t\right)$ and $\Phi\left(x_t\right)$, respectively, the prospect value for each farm is defined by

$$V_i = \sum_{t=1}^{m} v\left(x_t\right)\Phi\left(x_t\right) \tag{2}$$

The value functions in the gain and loss domains are:

$$v^+(x) = x_t^{\alpha^+} \tag{3}$$

$$v^-(x) = \lambda x_t^{\alpha^-} \tag{4}$$

parameters α^+ and α^- are associated with the scale of value in the gain and loss domain, respectively and λ denotes loss aversion level.

The calculation of decision weight $\Phi\left(x_t\right)$ is based on the distribution of incomes from past income values. Assuming that historical incomes follow normal distribution over a given memory length m, we can identify the cumulative distribution function of income x_t, denoted by $F\left(x_t\right)$. Based on this assumption of normal distribution, we then calculate the decision weight of each income. In the case of income x_t is a gain, that is, its value is higher than the reference income, the decision weight for the income is given by

$$\Phi_{x_t}^+ = w^+\left[1 - F\left(x_t\right)\right] - w^+\left[1 - F\left(x_t + \Delta\right)\right] \tag{5}$$

where w^+ is the probability weight function in the gain domain, and Δ is the difference between an income value and its adjacent value, for example, 1 unit in the currency in which the income is expressed.

If income x_t is determined as a loss, that is, its value is below the reference income V_i^{ref}, the decision weight for income x_t, is

[2]All data and codes are available in R. Huber, H. Xiong, K. Keller and R. Finger (2020). *FARMIND: FARM Interaction and Decision-making Model.* ETH Research Collection, Zürich. https://doi.org/10.3929/ethz-b-000456722.

TABLE 2 Characteristics of FARMIND agents for the calculation of strategic heuristics

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}
Social network	Number of peers a farmer is linked to (number of ties)	n
	Weight of ties (strength of linkage to peers)	β_n

$$\Phi_{x_i}^{-} = w^{-}\left[F\left(x_t\right)\right] - w^{-}\left[F\left(x_t - \Delta\right)\right] \tag{6}$$

where w^{-} is the probability weight function in the loss domain.

Based on Tversky and Kahneman (1992), Camerer and Ho (1994), and Wu and Gonzalez (1996), probability weight functions w^{+} and w^{-} are

$$w^{+}(p) = \frac{p^{\varphi^{+}}}{\left(p^{\varphi^{+}} + (1-p)^{\varphi^{+}}\right)^{1/\varphi^{+}}} \tag{7}$$

$$w^{-}(p) = \frac{p^{\varphi^{-}}}{\left(p^{\varphi^{-}} + (1-p)^{\varphi^{-}}\right)^{1/\varphi^{-}}} \tag{8}$$

Thus, the prospect value is calculated using agent specific value and probability weighting functions for each income over the memory length m. If the sum of these incomes is positive (negative), an agent is considered to be satisfied (unsatisfied).

This formalisation of satisfaction has the following implication in the context of our weed control model. An agent does not merely assess the annual gross margin from maize production (myopic behaviour) but looks ahead at prospects over a predefined period to select a strategy for the next year. Thus, an agent may still be satisfied even though gross margins were low that year due to unfavourable conditions in weed emergence or low maize prices.

4.2 | Information seeking behaviour

In FARMIND, two different values are calculated to determine whether an agent adopts information seeking behaviour in reaction to disparities in economic performance and farming activities when compared to other agents. Disparity in economic performance may cause an agent to adopt a social information seeking strategy if the difference between his own income growth and the average income growth of the population at large g_i falls below an individual threshold g_i^{tol}. This implies that a gap between changes in the incomes of all the agents in general motivates the farmer to seek for information in his social network.

To determine g_i, we calculate the percentage of the income change $\mathrm{G_{i,t}}$ for year t and each farmer i over the farmer's memory length (m). We then compare this change between the individual farmer and all the agents in the model. Agent i's income growth for period t is

$$G_{i,t} = \frac{x_{it} - \frac{\sum_{t-m}^{t-1} x_i}{m-1}}{\overline{x_{i,\,m-1}}} \tag{9}$$

and the income growth of the entire population ($\overline{\mathrm{G_t}}$) is

$$\overline{G_t} = \frac{\overline{x_{t-1}} - \frac{\sum_{t-m}^{t-1} \overline{x_j}}{m-1}}{\overline{x_{m-1}}} \tag{10}$$

The income growth disparity is then given by

$$g_i = G_{i,t} - \overline{G_t} \tag{11}$$

If the difference between the individual and the average change in income exceeds an individual tolerance level g_i^{tol} (measured in percentage income growth), the farmer concerned adopts information seeking behaviour. This definition also implies that an event or crisis can prompt the farmer to reconsider their individual strategy and to think about other farming activities[3] (most recently: Foguesatto et al., 2020; Mishra et al., 2021).

In our weed control model, a disparity in income implies that a farmer will start social processing if they observe that the other farmers achieved a higher gross margin than expected whereas they did not. For example, a farmer may seek alternatives if, under a specific combination of environmental conditions, the weed control strategy he selected fails to perform as well as the strategies chosen by others. As the price for maize is the same for everyone, the gap in income change must be due to the weed control decision in that year. This prompts the farmer to study the weed control options applied by peers in their social network, or if really dissatisfied, they might even decide to stop cultivating maize in future. However, a social oriented behaviour does not automatically imply that a farmer will actually change their weed control practices. This also depends on preferences and the profitability of the alternative practices under the prevailing natural conditions (weed emergence and weather) and is addressed in the second and third modelling steps of FARMIND.

In addition to the observed economic performance, a farmer adopts a social information seeking strategy if their activity choices differ from those of their peers. This is described by the dissimilarity index d_i, which represents the farmer's inclination to consider behaviour that deviates from that of other farmers. A low dissimilarity tolerance level d_i^{tol} implies that a farmer is more likely to comply with peers. The dissimilarity with respect to farming activities is calculated by counting the average number of activities A performed in the agent network over the memory length. The average number for each activity performed by the agent and the network is then divided by all the activities performed in the corresponding network. Assuming that a activities are performed by all the peers in the social network, agent i's activity dissimilarity is

$$d_i = \frac{1}{a} \sum_{j=1}^{a} \frac{\#\ of\ peers\ performing\ A_j}{n} \left(1 - P\left(A_j^i\right)\right) \tag{12}$$

[3]This can also be connected to concepts like availability heuristics which tallies with empirical evidence that farmers' perception and decision-making can change due to recent experiences of extreme events (e.g., Foguesatto et al., 2020, Ding et al., 2009, Alem et al., 2010).

where $P\left(A_j^i\right)$ is agent i's performance status for activity j; $P\left(A_j^i\right) = 1$ if A_i is performed and otherwise $P\left(A_j^i\right) = 0$, and n is the number of peers to whom an agent is linked. The higher the value of d_i, the greater the similarity between an agent and their peers (measured on a relative scale with 1 implying all farms engage in the same activity). Please note that the agents' dissimilarity also depends on the size of the network n and the number of activities in the network a. The larger the network and the higher the number of activities within this network, the more likely it is that an agent will be dissimilar to their peers.

In our weed control model, an agent embarks upon social processing if they observe that their weed control option differs from that adopted by other agents. Thus, if they are the only agent using a mechanical weed control strategy (type III in Figure 2) and all the others in the network use glyphosate (type I in Figure 2), the agent will include this option when considering next year's strategy decision (next iteration). Again, the agent does not automatically adopt the weed control strategy, but merely considers it as an option.

4.3 | Determining preferred farming activities

In FARMIND, the strategic heuristics must be translated into choice sets that can be transferred to the sub-model using constrained optimisation. This is achieved by applying a fuzzy outranking method to narrow down the options available in the sub-model. The general idea is that an agent has clear preferences for certain farming activities, but he might have no particular penchants when choosing between others. A set of farming activities that an agent would most strictly prefer is identified based on a score for each activity and is subsequently ranked and determined endogenously using fuzzy outranking. FARMIND integrates three different criteria, which serve to rank farming activities and derive the score for each farming practice: (1) Subjective preferences for farming activities and/or production methods R_P. This information must be collected via surveys and is exogenous to FARMIND. (2) Preferences revealed by farmers' observed behaviour in the past. Assuming that this conforms with their own preference, it is more likely to have a higher position in the ranking R_L. This criterion is model endogenous and is acquired from the farming activities chosen in preceding iterations. (3) If an agent chooses to imitate farming activities that can be observed in their network, these activities get an additional weighting and are thus ranked above other farming activities not observed in the network R_S.

When calculating the final score for each farming activity, the weight of these criteria can be set exogenously by choosing a value between 0 and 1 for β_p (weight for subjective preferences), β_L (weight for activities used in the past), and β_S (weight for influence of peers). This allows the model to be fine-tuned—for example, if subjective preferences are not available, β_p can be set to 0 and the model can rely solely on the model endogenous parameters $\mathrm{R_L}, \mathrm{R_S}$.

$$R = \beta_P R_P + \beta_L R_L + \beta_S R_S \tag{13}$$

The value R assigned to each farming activity is then used as a criterion to determine so-called fuzzy concordance relations for each pair of activities. There are three types of relations: (i) indifferent, (ii) weakly preferred, and (iii) strictly preferred. If the difference between the normalised values of activity A_1 (with a higher value) and A_2 (with a lower value) $R^{A_1} - R^{A_2}$ is smaller than an exogenously set lower threshold q^- these activities are regarded as indifferent, that is, the agent has no preference between the two. If the difference is greater than the upper threshold q^+, 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 $[q^-, q^+]$, A_1 is weakly preferred over A_2. Formally, the matrix $f\left(A_1, A_2\right)$, describing the relation between the two activities A_1 and A_2, is defined by:

$$f\left(A_1, A_2\right) = \begin{cases} 0 & if\ R^{A_1} - R^{A_2} < q^- \\ \dfrac{\left(R^{A_1} - R^{A_2} - q^-\right)}{q^+ - q^-} & if\ q^- < R^{A_1} - R^{A_2} < q^+ \\ 1 & if\ R^{A_1} - R^{A_2} > q^+ \end{cases} \tag{14}$$

This calculation allows farming activities to be ranked in a list. FARMIND then uses a non-dominance score (ND) algorithm (Equation 14) that endogenously defines a small sub-set (as small as possible) of farming activities. A characteristic of the non-dominance score is that it reduces the number of activities to a small sub-set that is strictly preferred.

$$ND\left(A_1, X, f\right) = 1 - \underset{A_2 \in X}{maxmax} \left\{R\left(A_2, A_1\right) - R\left(A_1, A_2\right), 0\right\} \tag{15}$$

where X is the set of all activities, A_1 denotes the activity of interest, A_j denotes other activities in X and $f(A_1, A_j)$ denotes the fuzzy pairwise preference matrix. The non-dominance score results in a reduced choice set for each agent, which is then passed to the optimisation model.

In our weed control model, this implies that an agent can have specific preferences for one weed control type over another. For example, an agent may perceive the use of no-till practices in combination with the application of glyphosate as the most beneficial weed control strategy on his farm, regardless of gross margins. This exogenous preference setting implies that weed control strategies involving glyphosate are more likely to enter the choice set that is transferred from FARMIND to the weed control model. This likelihood depends on (i) the relative scale between the ratings for the different weed control options; (ii) the type of weed control options chosen by this agent in the past; and (iii) in the case of an imitating agent, on the occurrence of this weed control strategy among peers. Larger relative differences between weed control strategies increase the likelihood that the non-dominance score will identify a set of options that will always be preferred over the others.

5 | 'PROOF OF CONCEPT': ILLUSTRATING KEY FUNCTIONALITIES OF FARMIND

In this section, we provide two examples of agent behaviour using the FARMIND framework. This demonstrates the functionality of FARMIND in linking behavioural economic research with standard bio-economic modelling approaches. To this end, we apply FARMIND to test two different hypotheses addressing these key functionalities of FARMIND, that is, social networks and risk considerations. We next describe the simulation setup, that is, the initialisation of our ABM (Section 5.1). We then illustrate how behavioural assumptions lead to a diversification of weed control strategies (Sections 5.2 and 5.3) and how these strategies, in turn, result in different economic (i.e., total gross margin) and environmental (i.e., total area of glyphosate-free acreage) outcomes in our case study region (Section 5.4). In addition to this 'proof of concept', we also performed a comprehensive sensitivity analysis. Because this contribution focuses on the description of the FARMIND framework, we refrain from presenting the sensitivity analysis in the main text. However, the results of this analysis are presented in Appendix SB and its implications are reviewed in the following section.

5.1 | Simulation setup

To initialise our simulations, we first generate a baseline scenario in which all agents optimise their weed control decision (see ODD protocol in the Appendix SA, Figure A2). In this case, approximately one-third of the agents apply a weed control strategy that includes glyphosate, which approximates observed levels in our case study region (Antier et al., 2020; Böcker et al., 2020). This baseline scenario allows us to test and compare two different simulation setups that illustrate the effect of social networks and individual, risk adverse behaviour respectively.

In the first simulation setup, we define two distinct specifications for social networks and then analyse how their configuration affects the diffusion of a dominant weed control option when agents imitate the behaviour of their peers. First, agents are grouped into a network according to their income maximising choice—that is, the weed control activity in the baseline scenario—and the initial activity is still randomly assigned according to the average shares of scenarios in Böcker et al., (2018). The hypothesis surmises that this kind of network enables agents to learn quickly and identify their best options by imitating those peers who have already been successful using this strategy (see e.g. Bakker et al., 2021). Secondly, agents are grouped in a network in which they are only linked to peers with the same initial activity. In this case, the income maximising activity, identified in the baseline scenario, is absent in the network and consequently there would be no diffusion. However, we implant one 'seed' agent who pursues an income maximising activity without glyphosate use within this otherwise closed network. Thus, given the heterogeneous agent parameterisation, this individual agent represents the starting point from which the other agents' optimal choice emerges through the simulation. This simulation reflects the diffusion of a previously unobserved weed control option in a network in which the outcomes are assessed not only based on agent or network properties but also depend on the location of specific agents in the network, that is, a structurally explicit analysis of social networks (as defined by Will et al., 2020). However, it must be noted here that the networks are set exogenously and that farmers may change their choice of weed control option but do not create new or change existing networks (see ODD+D protocol in Appendix SA).

The effect of heterogeneous risk preferences and farmers' preferences for a specific weed control option are modelled in a second simulation setup. To this end, we compare risk neutral to risk adverse agents. Risk neutral agents' risk preferences are set to 1 so that the satisfaction level is calculated based on their profit only. We then adjust the risk preference parameter to the values used in Tversky and Kahneman (1992), which trigger different behaviour in FARMIND. In addition, we set agents' preferences so that they prefer a no-till weed control option, that is, the application of glyphosate as a pre-sowing strategy. This simulation reflects the dynamics of individual risk-avoiding behaviour such as prophylactic use of pesticides with varying output price and yield levels, which affect the choice of weed control option (Möhring, Wuepper et al., 2020; Bakker, Sok et al., 2021).

In both setups, we run our model 10 times over 12 iterations (i.e., years in this case). We assume that the output prices for maize varies for each iteration but we keep the same yield levels in the different iterations. Thus, the variation in weed control strategies arise from price variations in the weed control model only. Please note that these applications aim to demonstrate the specific functionalities that FARMIND can add to existing bio-economic models. Despite the empirical basis of the weed control model, the results presented here do not represent empirical case studies and are purely artificial (although they would be of interest in follow-up studies).

5.2 | Role of social network in the diffusion of weed control options

Our application shows that the underlying social network affects the diffusion of a dominant weed control option when agents imitate the behaviour of their peers. The network is set so that a tie is assigned to each agent who seeks to optimise by performing the same type of weed control activities. This means that the farmer who is considering imitation will seek information from other agents who are likely to choose the same activity under optimising behaviour, for instance because they produce maize under similar environmental conditions. This simulation setup leads to a diffusion of the most profitable weed control option in the network (Figure 3a).

The results show a development path through the network because it takes several iterations until all the agents finally adopt their optimal strategy under given weed pressure and yields, that is, the weed control option in the baseline scenario. The lag in adoption is based on the relative measure of income disparity. Some agents do not start imitating until a certain number of their peers have changed their strategy and achieved increases in their income. In Figure 3b, we assume that agents are only linked to those peers who pursue the same activity, except for one agent (using herbicide in the post-sowing weed control option) who is linked to others who do not apply this weed control option at the beginning of the simulation. Implanting a seed into this closed network leads to a different diffusion pattern because the uptake of herbicide weed control is lagged as the agents must first be able to observe this behaviour in their network. In addition, the seed agent's activity is also diffused to other agents, leading to a further reduction in glyphosate use in our model. Finally, we see much less variability because agents have fewer alternatives in a small network.

5.3 | Role of risk preferences in choice of weed control options

In addition, we look at the effect of risk preferences in FARMIND. We compare agents with heterogeneous threshold values, but with all cumulative prospect theory parameters set to 1, that is, they consider their maximal income to calculate satisfaction (Figure 4a) and with risk averse farmers (Figure 4b).

Assuming that they can maximise their income, the number of agents who do not apply glyphosate pre-sowing remains more or less constant. However, the biases introduced by considering the cumulative prospect theory triggers different behaviour in FARMIND. The initial jump in the number of agents who opt out is larger because dissatisfaction is greater among risk-averse agents than among those who are risk neutral. This involves roughly 5% of the agents, which is in line with observations from the sensitivity analysis. Because we also assume that farmers will prefer pre-sowing glyphosate application over other weed control options, the number of agents who always use glyphosate increases slightly at the expense of agents who adopt mechanical weed control options. Thus, risk preferences in FARMIND generate different strategic choices that, when combined with assumed preferences, explain the choice of glyphosate over other weed control options in our simulation.

5.4 | Simulated effect of behavioural factors on glyphosate free maize acreage

The net effect of our simulation (i.e., the emerging economic and ecological outcomes of the simulation) implies that the total area of glyphosate free acreage varies between the different setups but has no large effects on the total gross margins of maize production (Figure 5). The rather small economic effect of different weed control options is in line with earlier analysis in our case study region (Böcker et al., 2018; Böcker et al., 2020). The income level is clearly influenced by yield levels and price ranges but less by the choice of different weed control options.

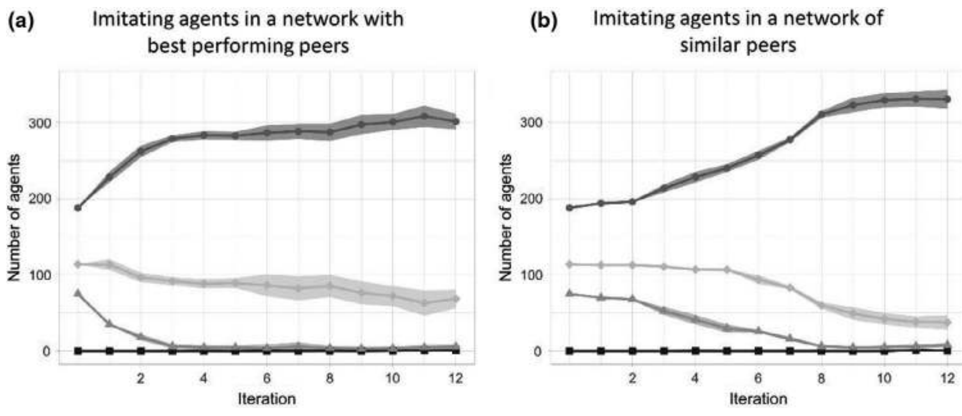

FIGURE 3 Changes in the choice of weed control activities with different social networks. Notes: The levels of grey represent different weed control strategies over one year in maize production, i.e., farming activities with pre-sowing glyphosate application (light grey), without pre-sowing glyphosate use (dark grey), mechanical weed control (grey) and abandonment of maize production (black). Points refer to the mean number of agents (total n = 377) choosing the corresponding activity over 10 simulation runs (output price range €3–4 per deciton). The shadings refer to the standard deviation of the 10 runs (with 12 iterations). Activities are randomly assigned to agents. Panel a: agents are grouped in a network according to their income maximising choice (average network size per agent =200). Panel b: a network in which agents are only linked to peers with the same initial activity (average network size per agent =40) except for the agent who opts for the income maximising choice. Starting from this individual agent, the optimal choice of the agents emerges through the simulation

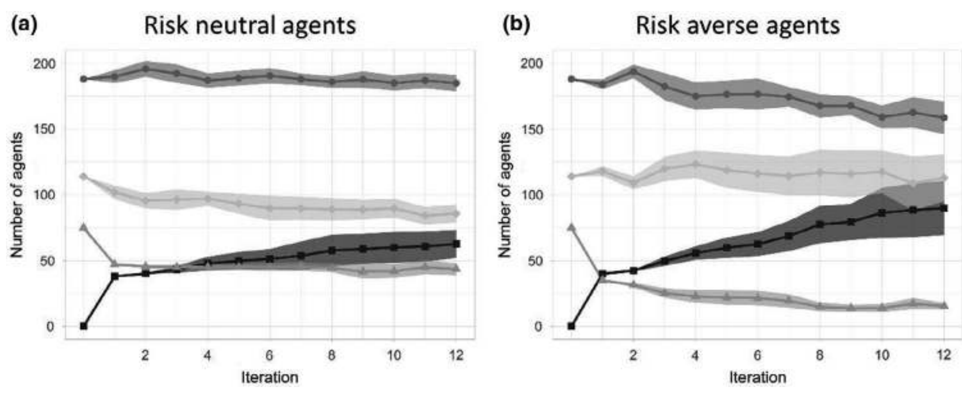

FIGURE 4 Changes in the choice of weed control activities with different parameter settings for agents' risk behaviour. Notes: The colours represent different weed control strategies in maize production, i.e., farming activities with pre-sowing glyphosate application (light grey), without pre-sowing glyphosate use (dark grey), mechanical weed control (grey) and abandonment of maize production (black). Points refer to the mean number of agents (total n = 377) choosing the corresponding activity over 10 simulation iterations (output price range €3–4 per deciton). The shadings refer to the standard deviation of the 10 iterations. Activities are randomly assigned to agents. Panel A: Agents' satisfaction is calculated based on income maximisation. Panel B: Agents are highly risk averse and prefer using weed control options containing glyphosate

With respect to the environmental outcomes, however, our setups show that behavioural factors might explain different levels of environmental stresses in maize production. In our case study, a reduction in glyphosate use decreases the overall toxicity but raises energy demand due to an increase in mechanical weed control measures (Böcker et al., 2020). In our first setup, we show that the location of specific agents in a network affects the diffusion of a specific weed control option (Will et al., 2020). In the case in which agents imitate the optimising

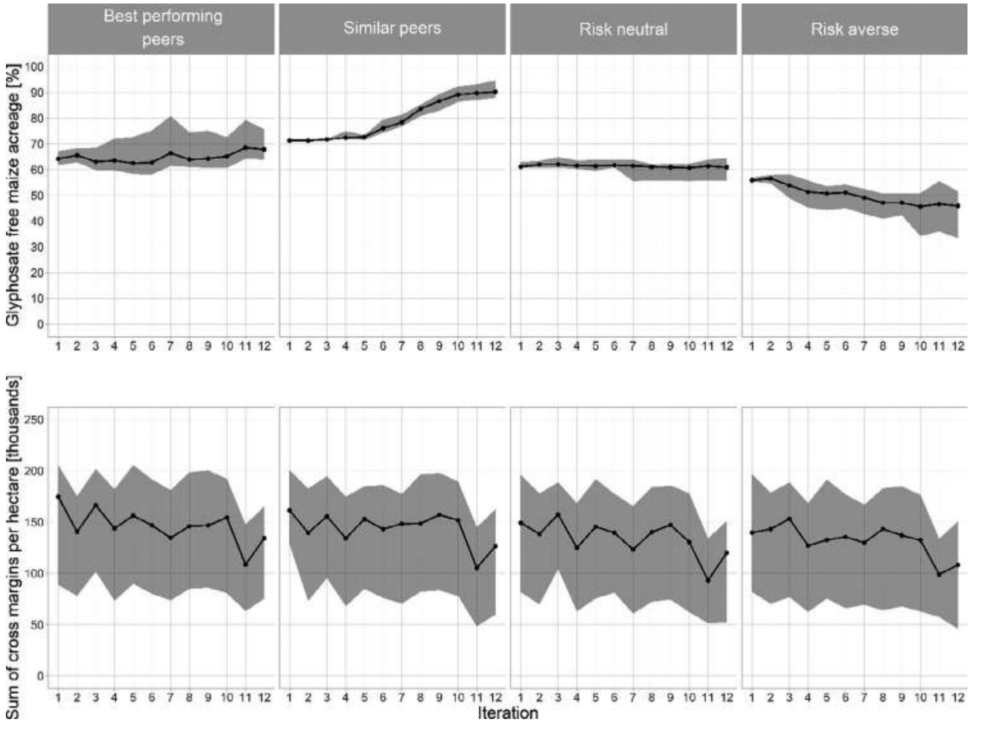

FIGURE 5 Changes in glyphosate free maize acreage and total gross margin (in 1000 euros) over 12 iterations and 10 model runs. Notes: Points refer to the mean percentage of total maize area and the sum of gross margins in 1000 euros over all agents and 10 simulation runs. The shadings refer to minimum and maximum values of the 10 runs

behaviour of their peers, the environmental effect resembles the baseline scenario in which all agents optimise. In the case, in which the weed control option with glyphosate is not available to all peers, the total acreage of glyphosate free acreage increases. Thus, the diffusion of weed control options with lower overall toxicity depends on the available options and knowledge in the social network underlying our simulations. This reflects the importance of knowledge and information in pesticide use decisions (e.g., Bakker et al., 2021).

The simulations in our second setup show how preferences and risk parameters might counteract the effect of peers on the use of glyphosate in our case study region. In this case, individual behavioural factors would lead to a continued use of glyphosate as a weed control strategy. Although the effect on total gross margin would be small, the overall toxicity in maize production would increase. This reflects the inertia in adoption of better weed control options based on individual risk-avoiding behaviour (e.g., Dessart et al., 2019).

6 | DISCUSSION

6.1 | Including diverse behavioural factors in modelling farmer decision-making

In the following, we discuss these three steps and the results from our simulations with respect to the conceptual framework, the strategic heuristics including social networks, cumulative prospect theory and farming preferences.

6.2 | Conceptual framework

From a conceptual perspective, this framework allows the strengths of bio-economic farm optimization models, that is, the detailed representation of economic and environmental outcomes, to be combined with the individual behaviour of farmers. In principle, a segregation of different decision steps using mathematical optimisation models had already been applied in early agricultural ABMs (Balmann, 1997; Berger, 2001). However, the modular setup of FARMIND allows the first-tier strategic decision to be combined with different types of bio-economic optimisation models containing income and farming activities as output. Consequently, FARMIND can be linked to numerous bio-economic farm models (see e.g., Ciaian et al., 2013; Reidsma et al., 2018; Shrestha et al., 2016; van Wijk et al., 2012 for reviews) depending on the research question at hand. It would even be possible to link the first strategic decision-level to existing agricultural ABMs, that is, MP-MAS (Schreinemachers & Berger, 2011) or AgriPoliS (Brady et al., 2017; Brady et al., 2009), which usually apply a complex, but uniform, type of decision-making. This attribute differentiates FARMIND from other generic ABM frameworks, such as Aporia (Murray-Rust et al., 2014). FARMIND's modularity could help to counteract the necessity to build models from scratch (O'Sullivan et al., 2015) and even allow the use of model components that are possibly beyond the reach of the development team. This can help to obtain more generalisable output from ABMs (Magliocca et al., 2015; Schulze et al., 2017).

However, we are aware that including behavioural factors do not automatically increase the representation of emergent properties on the system level and that validation, for example, the fit to observed macro-scale outcomes is a challenge in ABMs (e.g., Schulze et al., 2017). In this context, our 'proof of concept' shows that FARMIND can simulate diverging outcomes based on individual behaviour and the behaviour of peers. This is important as recent research shows that a reduction in farmers' pesticide use is highly influenced by the expectations of other farmers' behaviour (Bakker et al., 2021) and that farmers' beliefs and values play an important role in decision-making (Brown et al., 2020).

6.3 | Strategic heuristics

The strategic decision is implemented using the CONSUMAT strategies, that is, repetition, optimisation, imitation or opt-out based on the calculation of farmers' satisfaction and whether they adopt individual versus social oriented information seeking behaviour. The advantage of using this approach is twofold. First, these strategies are based on a valid and methodologically sound modelling framework that permits the integration of different theoretical concepts, such as decision strategies, cognition and social interaction (Schaat et al., 2017), which are important perquisites in ABMs (Brown et al., 2016; Jager, 2017; Schlüter et al., 2017). Secondly, it is possible to vary the behaviour of the agents, both endogenously and dynamically, over model iterations (Schaat et al., 2017). This is in line with various theories asserting that the same agent will use different decision-making modes depending on the type and context of the decision (Meyfroidt, 2013). Consequently, there is no predefined number or share of agents that always obey the same uniform decision rule in FARMIND. In our first simulation setup, for example, many agents do repeat their decision until the adoption of a weed control strategy in their network triggers them to imitate the choice of their peers.

Information seeking behaviour in FARMIND involves the strategic decision which is influenced by the growth rate of the agent's income compared to all other agents in the model and the dissimilarity of agricultural activities within the agents' network. When comparing income changes, the agents in the ABM by Morgan and Daigneault (2015) and Polhill et al., (2001) exhibit a similar mechanism, namely they compare their own profitability or yield with that of their peers and this in turn influences the probability that they adopt imitation behaviour. Although this approach is useful to trigger information seeking behaviour in FARMIND, it must be noted that the current implementation does not allow to consider skewed distributions of income changes. This assumption should be tested in real world applications of FARMIND and adjusted if necessary.

Dissimilarity in agricultural farming activities has also been applied in other ABMs for soil conservation efforts in Kenya (Van Oel et al., 2018) and household decision-making in Vietnam (Le et al., 2008). Other applications that employ the CONSUMAT strategies define uncertainty as a ratio between the realised income (or utility) and the mean of these values over the agents' memory length (e.g., van Duinen et al., 2016; Malawska & Topping, 2016; Pacilly et al., 2019). However, agricultural incomes are usually volatile due to climatic or market variations and farmers would expect this variability. In years with high deviations from the mean, farmers in these existing models would automatically exhibit uncertainty. Therefore, they would engage in socially oriented information seeking even though they are used to expecting this variability. Thus, the advantage of FARMIND compared to other ABM with dynamic decision-making is that information seeking behaviour is modelled endogenously and is not merely driven by exogenous assumptions about price and yield developments. This reflects farmers' individual decision-making more realistically and is in line with existing concepts such as expected utility, the cumulative prospect theory or state contingent approaches.

Our 'proof of concept' shows that such information seeking behaviour in FARMIND, triggered by comparing incomes or activities in different networks, influences the diffusion of weed control strategies in our simulations. Thereby, the conceptual framework allows for a structurally explicit analysis of social networks, that is, the consideration of the location of specific agents in the network. Thus, the consideration of such network effects in model-based assessment of pesticide use adds important information to the assessment of policy intervention (e.g., Grovermann et al., 2017).

The strategic decision associated with the satisfaction level implies that farmers do not start to search for better opportunities as long as they can meet their needs (Dressler et al., 2018). Our simulations with respect to the network that includes the farms with their income maximising choice (Figure 3) illustrates how this might lead to a delay in the adoption of weed control strategies. In general, this relates to satisfaction seeking behaviour and the 'change delay' applied in a few agricultural ABMs (Anastasiadis & Chukova, 2019; Gotts et al., 2003; Polhill et al., 2013). In this context, the use of strategic heuristics in a stepwise modelling approach may also attenuate the tendency of programming models towards overshooting in case of volatile returns—at least on the aggregate level.

6.4 | Cumulative prospect theory

We use cumulative prospect theory to calculate satisfaction, thus including risk preferences and subjective probability ratings in the decision-making process. FARMIND allows for the risky nature of agricultural production and recognises that risk attitudes are inherently an individual attribute (Hardaker & Lien, 2010). The role of risk and uncertainties in farmers' decision-making is described and understood from a normative perspective. Therefore, FARMIND can be used to test and develop hypotheses about farmers' behaviour in the context of counterfactual analysis or the implementation of new agri-environmental policy measures. Moreover, it builds a bridge to recent empirical applications of the cumulative prospect theory in agriculture (e.g., Bontemps et al., 2020; Iyer et al., 2020) and addresses the challenges in understanding decision-making under uncertainty, which cannot be identified from empirical data (Hellerstein et al., 2013; Just & Just, 2016).

Although many ABM consider risk or uncertainty (e.g., Bell et al., 2016; Berger et al., 2017; Maes & Passel, 2017), prospect theory has hardly been used in agricultural ABM and it is difficult to compare our results to existing studies. Given the high importance of risk in agricultural production, the consideration of cognitive biases with respect to decision-making under uncertainty may add an important level of detail to the simulation of agricultural systems (Howley et al., 2017). Considering the cumulative prospect theory in simulating farmers' decision-making has shown that it can improve the correlation between observed and simulated land-use data and farmer behaviour (e.g., Appel & Balmann, 2019; Bontemps et al., 2020). The advantage of FARMIND is that it allows both the expected utility theory and prospect theory decision rules to be considered in the same simulation, which provides an important entry point to diversify the representative agent model that assumes only one type of decision process (Harrison & Rutström, 2008). With respect to our simulation, the 'proof of concept' implies that considering such risk parameters affects the extent of glyphosate free acreage in our case study region without a large reduction in gross margins. Thus, considering such individual behavioural components might be an important feature in assessing policy interventions that aim to reduce pesticide loads (e.g., Möhring, Ingold et al., 2020). In addition, recent research also finds that farmers are more averse to uncertainty than risk (Cerroni, 2020) which could also provide an interesting starting point for the application of FARMIND.

6.5 | Farming activity preferences

The consideration of dispositional factors, such as preferences, is a central aspect of agricultural ABMs (An, 2012). Fuzzy preference maps are used here to consider farmers' preferences (or aversion) for certain farming activities. This links to survey-based farm or household typologies implemented in many agricultural ABMs (e.g. Grêt-Regamey et al., 2019; Holtz & Nebel, 2014) and permits an explicit consideration of part-time farming activities. In addition, the use of a fuzzy approach has two advantages. First, it allows the inclusion of the uncertainties associated with the collection of these subjective preferences (Dubois & Perny, 2016). Secondly, we assume that farming activities performed in the past indicate revealed preferences for these activities and therefore increase the probability of strict preferences for familiar practices over other/new activities. This increases the robustness of (subjectively stated) individual preferences. The importance of such preferences is illustrated in our last simulation in which the glyphosate free acreage decreases. Sticking to certain weed control options might reduce the knowledge gain from other available options and thus have an important impact on policy incentives.

The recursive update of the fuzzy preference maps in combination with the social network allows the implementation of learning mechanisms. This would allow to consider managerial abilities that have rarely been considered in agricultural ABMs or only as an uncertainty factor in simulation designs (e.g., Grêt-Regamey et al., 2019; Happe et al., 2006). Although there are a few models that explicitly address learning and dynamics of social networks in agriculture (Latynskiy & Berger, 2017; Manson et al., 2016; Rasch et al., 2016), the important mechanism in FARMIND is that a farming activity, which has been successfully pursued by farms within a social network, is not automatically imitated/adopted. The experience gained from past farming activities merely leads to an increase of the farmers' options. The actual decision—for example, whether to imitate or not—is simulated in the constraint optimisation problem considering the essential agronomic, economic and political constraints at farm level, that is, fodder and nutrient balances, labour and capital availability.

6.6 | Model uncertainty

One of the great challenges in agent-based models is their transparent presentation (An et al., 2020). ABMs become complex and their model outcome uncertain (Sun et al., 2016) due to the disaggregation into heterogeneous agents and the many processes involved. Thus, readers must be informed about the model uncertainty and the robustness of results must be assessed (e.g. Troost & Berger, 2015). It follows that a comprehensive sensitivity analysis is useful to address the uncertainties in model structure and parameterisation (e.g. Berger & Troost, 2014). It is essential to select the appropriate sensitivity analysis based on the purpose of the model (e.g. Ligmann-Zielinska et al., 2020).

We performed a comprehensive sensitivity analysis of FARMIND following Thiele, Kurth and Grimm (2014) and applied three consecutive analyses: Morris screening, standardised regression coefficients and Sobol's method (see Appendix SB). The sensitivity analysis shows that threshold values are key parameters in FARMIND, that is, the values that determine whether the agent is satisfied or not and whether an individual or a social information seeking strategy will be adopted. In general, the reference income is more important for individual focused behaviour, that is, optimisation and repetition. Tolerance levels for activity dissimilarity or income gap are more relevant in social oriented strategies such as imitation and opt-out. Depending on the underlying initialisation, up to 20% of the model variability may be explained by the parameters derived from the cumulative prospect theory that are used to calculate satisfaction in FARMIND. Thus, satisfaction levels can have a relevant impact on the model results even though they are only indirectly affected by the parameters of the curvature of the value function and the subjective probability rating parameters.

This sensitivity analysis is a helpful step towards understanding the model. It shows the robustness of FARMIND with respect to meaningful parameter ranges and different initialisations of the model. However, we are aware that our sensitivity analysis is based on an artificial setup. Although the underlying data with respect to maize production in our case study region is empirically grounded, our 'proof of concept' does not include an explicit validation exercise that would be necessary for future applications of our model (see e.g., Augusiak et al., 2014). Thus, future real-world applications of the FARMIND modelling approach would also need an extensive sensitivity and uncertainty analysis. For example, Troost and Berger (2015) not only assess the structural and parameter uncertainty of MPMAS, but also the uncertainties arising from model calibration, for example with respect to simulated and observed outcomes as well as future developments such as trough scenario analysis. In addition, the analysis should also explore the sensitivity to different formulations of certain sub-models (Schulze et al., 2017). This represents a crucial next step when applying FARMIND to real behavioural data. This would allow to decompose the different sources (behavioural, structural, environmental) that affect farmers' decision-making.

6.7 | Challenges

The integration of behavioural factors in farmers' decision-making in bio-economic models using FARMIND raises two major challenges. First, the parameterisation of agents is extremely data intensive and relies on surveys, economic experiments or interviews. Although an increasing amount of information is available about farmers' risk preferences, attitudes and values, a full parameterisation of all parameters in FARMIND for real world applications may be difficult and costly. Thus, the collection of empirical data must be aligned with the modelling purpose and the research question at hand (Schulze et al., 2017). Moreover, the importance of the threshold values implies that the identification of individual risk attributes must be based on multiple reference points to better identify producer decision-making (Tonsor, 2018).

The dependence on empirical data availability is a common challenge in agricultural ABMs, especially in cases where there is a trade-off between realistic assumptions on agent behaviour and model-related computational efficiency (Sun et al., 2016). Thus, empirical applications of FARMIND may remain restricted to smaller case studies rather than large-scale simulations, that is, at the large regional, national or European level.

Secondly, our approach is prone to equifinality—the generation of the same model output under different conditions (Poile & Safayeni, 2016; Williams et al., 2020). This makes it challenging to find the appropriate level to verify the output because different model parameterisation at the agent scale can lead to the same emergent outcome on the system level (Schulze et al., 2017). This implies that a good fit between observations and model results does not necessarily indicate that model parameterisation is correct (van Vliet et al., 2016). Our application shows that the flexibility of the model allows the simulation of development paths of agricultural production under different parameter combinations. Although the explicit theoretical basis of our approach somewhat attenuates this tendency, the performance of an extensive sensitivity and uncertainty analysis is absolutely essential (Poile & Safayeni, 2016; Saltelli et al., 2019) and expert and stakeholder knowledge must be included in applications of FARMIND (e.g. Millington et al., 2011).

Despite these challenges in model analysis and output verification, we are convinced that with more data-driven calibrations our 'proof of concept' will also be useful for real-world applications in the future. The main benefit would be to not only compare model outcomes with empirical observations on the individual or system level but also to quantify the relative impact of different factors determining these outcomes, such as the impact of individual behaviour compared to social networks or underlying farm characteristics (see e.g., Drechsler, 2021 for an application). The strength of ABMs such as FARMIND in this context is their ability to apply theoretical concepts (here cumulative prospect theory and social networks) to processes and conditions that empirical data and optimising models alone cannot cover (Brown et al., 2020).

7 | CONCLUSION

Modelling various human behaviour patterns can contribute to the counterfactual assessment of policy, technology or environmental changes (Grêt-Regamey et al., 2019). The agent-based model component FARMIND presented here provides a link between three important behavioural factors: risk, social networks and preferences for farming activities, and bio-economic models of agricultural production. It represents a conceptually sound starting point to inject diverse behaviour of farmers into existing models and thus represents a supplement to ongoing agricultural systems modelling. The model integrates the cumulative prospect theory and social networks with other key processes that capture human decision-making without modelling the cognitive process itself (Balke & Gilbert, 2014; Schaat et al., 2017). This also forms a link between modelling efforts that integrate different psychological mechanisms in the representation of farmers' decision-making and ongoing research in behavioural economics.

As in other agricultural ABMs, the availability of empirical data (Sun et al., 2016) represents a challenge when implementing a detailed representation of farmers' individual decision-making. This means that FARMIND might well be restricted to smaller case studies. The use of big behavioural data, for instance from mobile phones or other information and communication technologies (e.g. Bell, 2017), could be a promising approach to this problem. In combination with machine-learning approaches (see e.g., Storm et al., 2019), this kind of big data could be integrated into agent-based modelling approaches such as FARMIND. Another more pragmatic approach would be to aggregate behavioural data into farm typologies (Brown et al., 2020; Malek & Verburg, 2020; Müller et al., 2020). The modular structure of FARMIND would permit the integration of such approaches and thus form the basis for testing behavioural strategies in different decision-making contexts, thereby opening a promising path for meta-studies or case-study comparison (Magliocca et al., 2015; Malek et al., 2019; O'Sullivan et al., 2016). In addition, rigorous sensitivity and uncertainty analyses combined with a clear theoretical basis are also indispensable in future applications of FARMIND to eliminate equifinality in the validation of the model (van Vliet et al., 2016; Williams et al., 2020).

A theory-based representation of farmers' diverse behaviour patterns in existing modelling efforts could complement the development of agricultural systems models and increase their policy relevance (Jager, 2017). Many existing mathematical programming models focus on rational decision-makers and expected utility as their underlying theoretical concepts. However, this may limit their value for agricultural policy evaluations (e.g., Saltelli, 2019). In particular, FARMIND provides an entry point for the simulation of counterfactual analysis associated with the adoption of environmentally friendly farming activities and new agri-environmental policy measures (Pe'er et al., 2019), diversification and off-farm labour market participation (Howley, 2015), or the issue of family farm succession (Breustedt & Glauben, 2007; Suess-Reyes & Fuetsch, 2016) all of which have crucial impacts on production patterns, environmental pollution and ecosystem service provision.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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