Huber, R., Bakker, M., Balmann, A., Berger, T., Bithell, M., Brown, C., Grêt-Regamey, A., Xiong, H., Le, Q.B., Mack, G., Meyfroidt, P., Millington, J., **Müller, B.**, Polhill, J.G., Sun, Z., Seidl, R., Troost, C., Finger, R. (2018):
Representation of decision-making in European agricultural agentbased models
Agric. Syst. **167** , 143 - 160

http://dx.doi.org/10.1016/j.agsy.2018.09.007

Representation of decision-making in European agricultural agent-based models

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Highlights

- Agent-based modelling is a suitable tool for improving the understanding of farmers' behaviour.
- Review 20 agricultural ABM addressing heterogeneous decision-making processes in the context of European agriculture.
- Considerable scope to improve diversity in representation of decision-making by combining existing modelling approaches.
- More coordinated and purposeful combinations of ABM and hybrid modelling approaches are needed.
- Results provide an entry point for collaboration of agent-based modellers, agricultural systems modellers and social scientist.

Abstract

The use of agent-based modelling approaches in ex-post and ex-ante evaluations of agricultural policies has been progressively increasing over the last few years. There are now a sufficient number of models that it is worth taking stock of the way these models have been developed. Here, we review 20 agricultural agent-based models (ABM) addressing heterogeneous decision-making processes in the context of European agriculture. The goals of this review were to i) develop a framework describing aspects of farmers' decision-making that are relevant from a farm-systems perspective, ii) reveal the current state-of-the-art in representing farmers' decision-making in the European agricultural sector, and iii) provide a critical reflection of underdeveloped research areas and on future opportunities in modelling decision-making. To compare different approaches in modelling farmers' behaviour, we focused on the European agricultural sector, which presents a specific character with its family farms, its single market and the common agricultural policy (CAP). We identified several key properties of farmers' decision-making: the multi-output nature of production; the importance of non-agricultural activities; heterogeneous household and family characteristics; and the need for concurrent short- and long-term decision-making. These properties were then used to define levels and types of decision-making mechanisms to structure a literature review. We find most models are sophisticated in the representation of farm exit and entry decisions, as well as the representation of long-term decisions and the consideration of farming styles or types using farm typologies. Considerably fewer attempts to model farmers' emotions, values, learning, risk and uncertainty or social interactions occur in the different case studies. We conclude that there is considerable scope to improve diversity in representation of decision-making and the integration of social interactions in agricultural agent-based modelling approaches by combining existing modelling approaches and promoting model inter-comparisons. Thus, this review provides a valuable entry point for agent-based modellers, agricultural systems modellers and data driven social scientists for the re-use and sharing of model components, code and data. An intensified dialogue could fertilize more coordinated and purposeful combinations and comparisons of ABM and other modelling approaches as well as better reconciliation of empirical data and theoretical foundations, which ultimately are key to developing improved models of agricultural systems.

1. Introduction

Governments strongly influence and support the agricultural sector in Europe and there is increasing interest in a critical evaluation of these policies. In this context, reliable explanatory models of agricultural systems are of key importance since they allow evaluations of effectiveness and efficiency of policy measures where empirical data is not (yet) available e.g. in climate change impact studies, modelling counterfactual scenarios of policy changes, or future market conditions. Understanding how farmers take decisions, including anticipation strategies, adaptive behaviour, and social interactions is crucial to develop such models (Berger and Troost, 2014; Janssen and Ostrom, 2006; Meyfroidt, 2013).

In recent years, agent-based models (ABM) have gained increasing popularity for modelling agricultural systems and the impacts of policies (e.g. Groeneveld et al., 2017; Kremmydas et al., 2018; Nolan et al., 2009). Agent-based modelling represents a process-based "bottom-up" approach that attempts to represent the behaviours and interactions among autonomous agents through which agricultural systems are evolving and thus to simulate emergent phenomena without having to make *a priori* assumptions regarding the aggregate system properties (Brown et al., 2016a; Helbing, 2012; Magliocca et al., 2015). Thus, agent-based modelling is a suitable tool for improving the understanding of farmers' behaviour in response to changing environmental, economic, or institutional conditions, particularly on the local level (An, 2012; Magliocca et al., 2015).

Agent-based modellers often choose to build new models from scratch (O'Sullivan et al., 2015) and take varying approaches, from microeconomic models to empirical and heuristic rules (An, 2012; Schlüter et al., 2017), whichever suits their purposes best. As a consequence, empirical data on farm decision-making collected for model building is often specific to one model, one geographic region, and the particular processes being represented. The key challenge is to ensure that, for sake of parsimony, the representation of decision-making in agricultural ABM is equipped with those properties and behavioural patterns of the farmer that are relevant for a given purpose, and no more or less (Balke and Gilbert, 2014).

The representation of farmers' decision-making crucially depends on the phenomena to be simulated and the purpose of the study. Modellers may abstract or ignore system properties in a specific modelling endeavour even though the corresponding mechanism is important from a conceptual perspective. Because no single approach is best suited to represent decision-making in general, comparing different research efforts can help to identify which particular agent decision-making representations are appropriate for particular model purposes (Parker et al., 2003). This could support more coordinated and purposeful combinations of ABM and other hybrid modelling approaches in the agricultural sector, which would lead to improved models of agricultural systems (O'Sullivan et al., 2015).

Model comparisons and reviews are frequent in land-use and land-cover ABM (Parker et al., 2008a; Parker et al., 2008b) and recently more generic and flexible modelling approaches such as agent functional types (Arneth et al., 2014; Murray-Rust et al., 2014) or agent-based virtual laboratories (Magliocca et al., 2014) have emerged. While these comparisons and reviews are very useful, they do not provide an in-depth analysis of specific models and its functionalities. Notably, a proper analysis and comparison of agents' decision-making in agricultural ABM with a specific focus on European agriculture and its specific policy context is lacking. The European agricultural sector with its single market and its common agricultural policy (CAP), fundamentally anchored in the concept of multifunctionality, provides a specific setting of economic and institutional conditions that allows for a meaningful comparison of different approaches in modelling farmers' behaviour. This setting is particularly distinct from that of subsistence farming in developing countries or very large farms in the US or Australia. With many researchers currently engaged in agricultural ABM in Europe, there seems to be a fruitful basis for more in-depth comparison of models within the same research domain and research focus.

Thus, here we reviewed existing ABM in the European agriculture context with a specific focus on the implementation of the farmers' decision-making process. The research questions are:

i) What are the specific properties of European farmer households that are believed to influence their decision-making?
ii) Which levels and types of decision-making mechanisms are represented in European ABM?
iii) Are the represented decision-making mechanisms related to specific problem domains in agricultural systems?

The review provides a first entry point for agent-based modellers, the broader community of agricultural systems modellers and data-driven social scientist for the re-use and sharing of model components and codes as well as for the identification of meaningful model comparisons in the context of farm systems analysis. This is the key to develop comprehensive models of agricultural systems and their use in ex-ante or ex-post agricultural policy evaluations. The paper is structured as follows. In a background section, we summarize existing reviews on decision-making in ABM and outline a farm-systems perspective on decision-making in agricultural ABM. We then describe the review process and the levels and decision types used for the description of the models. In the Results section we illustrate how the conceptualisation of decision-making varies by research question in agricultural ABM. Finally, we discuss our results with respect to ABM in general and outline future prospects for decision-making in agricultural ABM.

2. Conceptual background

2.1 Description of decision-making in ABM

Several recent reviews have classified the types of decision-making used in ABM in social-ecological or human-nature systems, either from an operational or a theoretical perspective. In his review, An (2012) classified the different theoretical approaches into nine decision models, ranging from microeconomic mechanisms to psychological and cognitive models. The ODD protocol is currently the standard for describing ABM, with a specific extension for human decisions ODD+D (Müller et al., 2013). The ODD protocol is structured in three basic elements i.e., overview, design concepts and details (Grimm et al., 2006; Grimm et al., 2010). According to ODD+D, the individual decision-making should be described by making explicit the subjects and objects of decisions, the levels of decision-making, rationality/objectives, decision rules and adaption, social norms and cultural values, spatial aspects, temporal aspects, and uncertainty. The protocol has already been used to compare different ABM land-use models (Groeneveld et al., 2017; Polhill et al., 2008) and agricultural ABM (Kremmydas, et al., 2018). The MR POTATOHEAD[1] framework has also been used to compare agent-based land-use models (Parker et al., 2008b). The framework distinguishes six conceptual classes; information/data, interfaces to other models, demographic, land-use decision, land exchange, and model operation. Compared to the more general ODD, MR POTATOHEAD enables a more detailed comparison of *land-use* related ABM.

With a stronger focus on theoretical aspects of the decision-making, the MoHuB (Modelling Human Behaviour) framework provides a tool for mapping and comparing behavioural theories of individual decision-making of a natural resource user (Schlüter et al., 2017). MoHuB distinguishes between the individual and its social and biophysical environment which interact through 'perception' of the environment and agents' 'behaviour'. The actual 'selection' process of behaviour depends on the 'state' of the agent which includes its goals, values, knowledge and assets as well as its 'perceived behavioural options'. The 'evaluation' of the consequences of an agent's behaviour on its 'state' closes the loop. The authors use this framework to describe different theories, including the concept of *Homo economicus*, bounded rationality, theory of planned behaviour, reinforcement learning, descriptive norms, and prospect theory (see Schlüter et al., 2017). Balke and Gilbert (2014) focus on the decision-making process within ABM, but not restricted to land-use or social-ecological systems. Their review is itself based on other classifications and reviews (i.e., Helbing, 2012; Meyer et al., 2009; Tesfatsion and Judd, 2006), and identifies cognitive, affective, social and norm consideration and learning as the key dimensions in describing and comparing human decision-making in ABM. A similar classification can also be found in Kennedy (2012).

In general, all of these classifications and frameworks can be used to compare the representation of decision-making in European agricultural ABM. Many of these frameworks, however, use different classes for describing similar aspects of the decision-making depending on their purpose (i.e., whether they offer practical guidelines to build, describe or compare ABM). In this study, we combined elements of the different frameworks in order to address the specific challenges of understanding (i) farm decision-making, (ii) its representation within ABM, (iii) and their use in the context of European agricultural systems (see Method section).

2.2 Agents' decision-making in farm systems

1 MR POTATOHEAD: Model representing potential objects that appear in the ontology of human environmental actions and decisions

The major advantage of ABM is their ability to consider heterogeneous agents and their interactions, along with feedbacks to simulate emergent properties of a system (Matthews et al., 2007). Thereby, ABM allow the representation of agent-specific behaviour covering individual preferences or motivations (An, 2012; Bruch and Atwell, 2015; Kelly et al., 2013). This is particularly relevant in the agricultural sector in which farming families are the main decision makers but differ widely, and whose decision-making often goes beyond income maximization (Feola and Binder, 2010; Levine et al., 2015; Meyfroidt, 2013). For many farmers, for example, farming is a vocation that is valued in itself and goals such as maintaining farming lifestyle, upkeep traditions or fulfilment of personal 'intrinsic' values i.e., enjoyment of works tasks or enjoyment of self-employment may be as important as economic drivers (Burton and Wilson, 2006; Gasson, 1973; Howley, 2015; Howley et al., 2017; Howley et al., 2014).

Recent publications in the context of social-ecological systems modelling (Filatova et al., 2013; Schulze et al., 2017), integrated assessment (Laniak et al., 2013), agricultural systems modelling (Jones et al., 2016) and policy impact assessments (Reidsma et al., 2018) suggest that there is a need for improved representation of farmers' heterogeneous decision-making. The representation should not only consider cognitive individual processes, personal characteristic, or social interactions (as in most non-agricultural ABM), but also the socio-economic and natural environment as well as farm household characteristics. This has four important implications that distinguish decision-making in farm systems from other agents typically represented in agent-based modelling.

First, decisions at the farm level are based on a multi-input and multi-output production functions (e.g. Ciaian et al., 2013; Shrestha et al., 2016). For example, farms often include crop and livestock production activities which are linked via manure or fodder balances. Thus, resources such as land, labour and capital must be allocated to different marketed and non-marketed products, with a high degree of uncertainty and risk stemming from markets or production conditions (Hardaker et al., 2015). As a consequence, technological and economic interdependencies (Abler, 2004) and risks and uncertainties play a crucial role in the agents' decision-making (Jager and Janssen, 2012).

Second, farmers' decisions are also often affected by non-agricultural activities (Rossing et al., 2007). For example, most family farms represent both a household and a business unit at the same time (Evans et al., 2006; Graeub et al., 2016). Thus, parts of both the income and labour of the family members may be allocated outside the agricultural sector (Benjamin and Kimhi, 2006; Weltin et al., 2017). As a consequence, opportunity costs of agricultural, non-agricultural and leisure activities have an important impact on the decision-making.

Third, decisions are typically not taken by a single person (Burton and Wilson, 2006). This is in part the origin of various emotional and cultural attitudes towards farming (e.g. keeping up a family tradition) and especially farm succession or exit (Darnhofer et al., 2016; Farmar-Bowers and Lane, 2009; Willock et al., 1999). In addition, for family farms, family structures and investment cycles interrelate with farm succession and exit rates. Moreover, consumption decisions are also of crucial importance on a household level (Weltin et al., 2017). The family-based, and thus atomistic, structure of most of the agricultural sector worldwide implies that collaboration, collective actions, and other networks are of crucial importance in decision-making. Empirical evidence shows that networks play a critical role in innovation and adaptation of agricultural practices (Moschitz et al., 2015; Schneider et al., 2012; Sol et al., 2013). Lastly, the representation of learning, knowledge-sharing and innovation within a family may be more complicated than in individual decision-making.

Fourth, farm(er) agents' decisions are often embedded in multiple temporal cycles. On the one hand, many of the agricultural production decisions are rooted in seasonal or annual production cycles. On the other hand, agricultural production activities imply the use of capital intensive assets that are used over longer periods. Moreover, several agricultural activities such as perennial crop and livestock production often naturally span different periods. Thus, investment decisions, sunk costs, and path dependencies play a crucial role in production decisions (Berger and Troost, 2014; Happe et al., 2008). Decisions on the buying or selling of land depend on the future prospects of the farm, and on the long-term strategy. Thus, the production decision always has short and long-term components. In addition, agricultural production is characterized by a natural lag between production decisions and realization of outputs, production cycles, and is soil-dependent, weather-dependent, and technology driven (Mehdi et al., 2018). While this may also hold for other economic sectors, the spatial aspect of these processes adds complexity via land tenure systems and neighbourhood effects.

In summary, the decision-making process on farm or farm-household level includes specific components and interactions which could be considered in ABM (see Jones et al., 2016 for a recent review of agricultural and farm systems modelling). Thereby, the structure of a conceptual whole-farm model integrates economic, ecological and social components (Dent et al., 1995). From a farm systems perspective, the multi-output nature of production and associated uncertainties, the importance of non-agricultural activities, the heterogeneous household and family characteristics, and the concurrent short and long-term decision-making context are important properties of farmers' behavioural patterns.

2.3 Farm and agricultural systems perspective in Europe

The specific characteristics of farmers' decision-making process is important in many contexts worldwide e.g., food security, climate smart agriculture, or natural resource use. To restrict the number of contexts and have a focused and in-depth discussion, we here focus on models applied in a European context. Agricultural systems[2] in Europe have a set of specific characteristics, and studies of European agriculture address questions that are specific to the European (multifunctional) context including farm structures, agricultural landscapes, and environmental impacts of farming (Van Huylenbroeck and Durand, 2003). Three specificities emerge from this European perspective:

- First, with the CAP and other European-level policy schemes such as Natura 2000, as well as national schemes, agriculture in Europe plays out in a very heavily regulated environment, one aspect of which is high levels of subsidisation (Swinnen, 2015). This results in policy priorities which try to achieve multiple objectives including increasingly prominent environmental targets (Pe'er et al., 2014). Thus, farmers' decisions are very strongly influenced by shifts in policy priorities and decisions on subsidies. This strong regulatory environment also plays out in land zoning. In most places, agricultural expansion is highly restricted in contrast to areas where agricultural expansion is a major process and focus of modelling such as parts of the tropics (Bithell and Brasington, 2009).
- Second, family farming units that dominate in European agriculture are both production and consumption units. These farms are, however, much more capitalized and embedded in market relations (both for inputs and outputs) and there is much more diversity in terms of access to and use of technology than typical subsistence oriented small family farms in developing countries (Meyfroidt, 2017). In contrast to North America or Australia, average farm size in Europe is much smaller (Eastwood et al., 2010)).
- Third, high opportunity costs of farming (e.g. for land and labour), low farming income as well as high legal constraints trigger two contrasting developments. On the one hand, highly productive

[2] We here define agricultural systems as a subordinate classification of the farm systems representing the complex interactions and interdependencies between farmers' individual production choices in divers cropping and livestock systems, natural systems (including climate, soil, or pests) and social structures such as markets and policies.

land in agglomerations and well-developed areas are increasingly under pressure of intensification. On the other hand, part-time farming and farm exit lead to extensification (de-intensification) and land abandonment in many marginal European areas (Breustedt and Glauben, 2007; MacDonald et al., 2000; Renwick et al., 2013). This causes political tensions between a productivist model of farming and attempts to shift farming into other directions, for example with an increasing relevance of economic diversification on and off the farm, e.g. tourism, on-farm processing and direct sales (Meraner et al., 2015; Wilson, 2008). In contrast to Europe's increasing focus on environmental benefits and diversification, a strictly productivist mindset might be much more prevalent elsewhere in the world.

Thus, for the simulation of phenomena such as food production, agricultural landscapes, land abandonment and environmental impacts in European agriculture, a specific set of research questions emerge about possible reactions to policy changes, farm exit and farmers' replacement and recruitment, and livelihood diversification. In summary, because European agriculture is already quite diverse (Levers et al., 2016), restricting our comparison here to models developed specifically for the context of European agriculture allows us to control partly for the variability in contexts, land uses and farm agents. At the same time, we maintain a relatively large number of models, and thus are able to better understand how differences in the representation of decision-making influences what can be learned from different models.

3. Method

Besides a thorough literature analysis, our review has been based on an iterative exchange between model developers, experts on decision-making and a core writing team. The core team developed a preliminary framework of decision levels and types (i.e., review criteria) to identify the properties of farmers' decision-making that matter in a systemic perspective on agriculture. Based on these criteria, developers described their existing models in detail. Next, the framework, decision levels and types, as well as future directions in European agent-based modelling, were discussed in a two-day workshop. Finally, the developers revised their description of the models, based on the workshop results and jointly commented the manuscript.

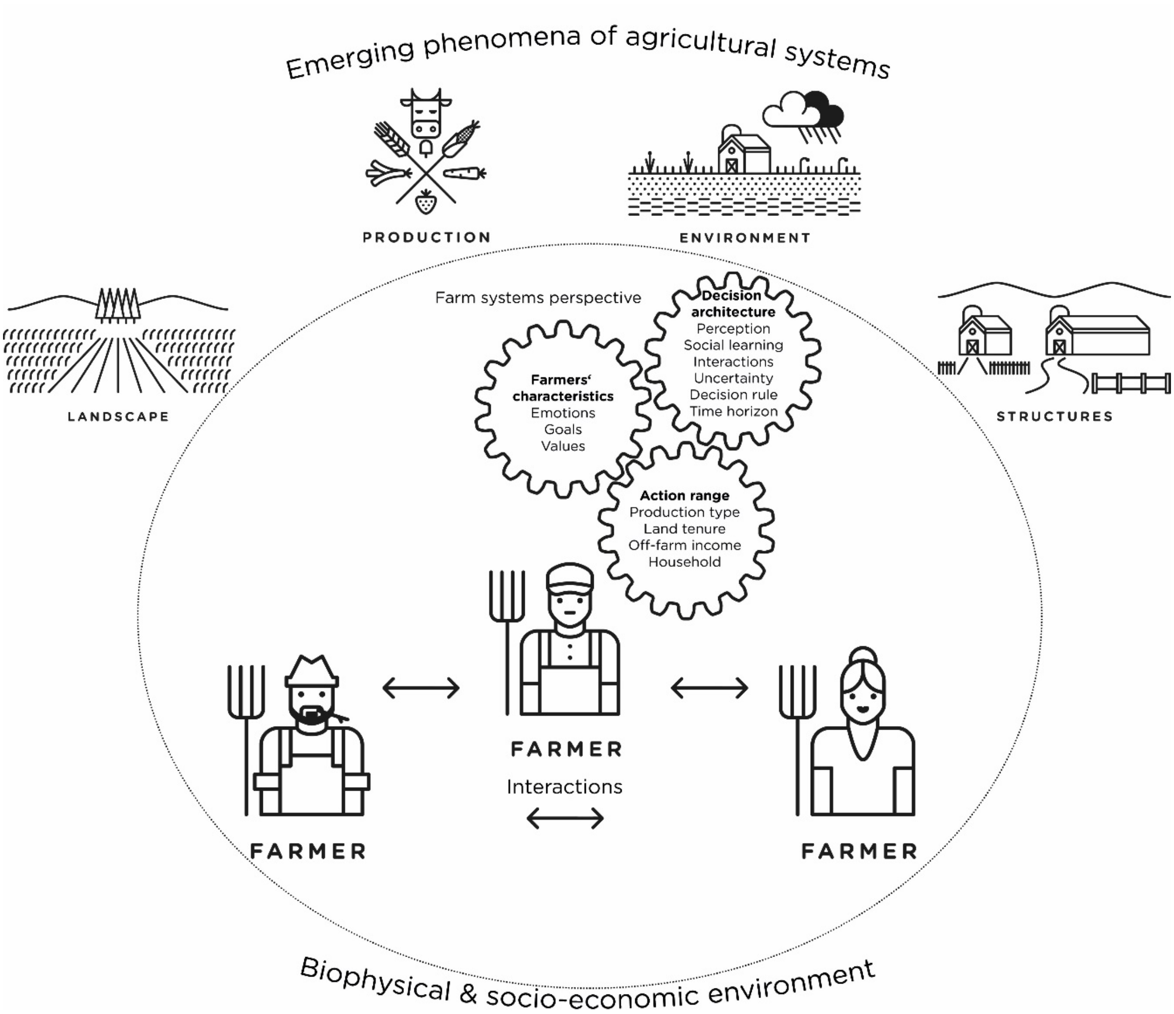
3.1 Literature search

To identify the relevant models, we first screened the list of models analysed in the review of agent-based land use models by Groeneveld et al. (2017). We selected all the models that addressed agriculture in a European context (11 models out of 134 publications). In addition, we did the following search in Scopus, Web of Science and Google Scholar to identify the relevant manuscripts: "Agriculture AND agent-based modelling"; "farm AND agent-based modelling". We selected all studies published in scientific journals and excluded all non-European studies (77 out of 193 publications). Finally, we checked whether the remaining articles included agents and some type of decision-making in their analysis. Through this literature search, we found 9 additional models (in 41 publications; for details see Appendix B Table 1) to produce a total of 20 models. In contrast to Kremmydas, et al. (2018), we explicitly included also land-use models that simulate farmers' decision-making and focused on models rather than publications.

3.2 Workshop

We invited the developers of the most prominent models and further experts on decision-making and agent-based modelling to a Workshop held in January 2017 (see Appendix A for a list of participants). The interaction between the experts ensured a critical assessment of review criteria as well as categorization of existing research. Moreover, the workshop ensured an extensive reflection on challenges and prospects of representing farmers' decision-making in agricultural ABM. For the preparation of the workshop, the developers described their models with respect to preliminary review criteria, creating a comprehensive summary comparison of European agricultural ABM (see Appendix B, Table 2 summarised and synthesized in Tables 3,4 and 5). During the workshop, three tools provided by the Network for Transdisciplinary Research were used to guide the discussions (see Appendix C). First, we used the Venn diagram tool (Td-net, 2016b) to elicit the main topics of research and their perspective on agent-based modelling approaches. This clarified each participant's expertise and research interest in relation to the implementation of farmers' decision-making in agricultural ABM. Second, we applied the Toolbox Approach (Eigenbrode et al., 2007; Schnapp et al., 2012) to uncover implicit assumptions and shared understandings of the scientific background of ABM in agriculture. One the one hand, this allowed us to identify shared views on relevant properties in farmers' decision-making. On the other hand, the tool revealed general challenges in ABM development which built the background for our discussion of the reviewed models. Third, we used a Give-and-take matrix (Td-net, 2016a) to identify pieces of knowledge or model components that could be shared between different workshop participants. This informed the future prospects in developing and applying agricultural ABM. The combination of the three methods for co-producing knowledge allowed us to categorize and collect existing research and thus build the foundation for our review. Based on the discussion in the workshop and the developers' model descriptions, we adjusted and extended initial model descriptions to account for the agricultural phenomena addressed (i.e., the purpose of the model). This gave on an overview of the existing use of ABM in the context of European agriculture.

Figure 1. Dimensions of farmers' decision-making and simulated emerging phenomena in European agricultural ABM



3.3 Review criteria

To answer the research questions, we reviewed the existing 20 models in two steps. First, we combined the constitutive elements of ABM identified in the different frameworks in Section 2.1 with the characteristic elements of the farming system in Section 2.2 and proposed an agriculture-specific framework to describe and compare different dimensions in farmers' behaviour in ABM. All 20 reviewed models were described using this framework (see 3.3.1). Second, we evaluated the representational sophistication in simulating farmers' decision-making by assessing eleven decision-making elements (see 3.3.2). The reviewed models were rated across three levels of model functionality, as defined for each criterion in Table 2. Finally, we investigated whether there was a match between certain decision-making elements and emerging phenomena in the modelling approaches, allowing us to identify patterns between emerging phenomena and the representation of farmers' decision-making.

3.3.1 Framework of important dimensions in agricultural ABM

The review framework we developed brings together the different elements of existing classifications by considering three basic elements (Table 1); overview criteria (which can describe any type of model), characteristic elements of ABM (which provide the standard criteria for agent-based modelling approaches), and the decision-making elements (which describe the specific implementation of the decision-making from a farm systems perspective). Details of these three elements are as follows;

1. *Overview*: We distinguished models with respect to the emerging phenomena they each addressed (e.g. land-use patterns, farm structures etc.), their purpose (e.g. explanatory with full empirical parameterization or explorative with theoretical motivation and partial parameterization) as well as their spatial and temporal extent (Table 3). In general, European agricultural ABM focus on production decisions and the resulting incomes, the development of farm structures, and environmental impacts or landscape changes (i.e., the emerging phenomena represented by the pictograms outside the modelling environment in Fig. 1). In addition, we provide information on the spatial extent of the model (in km^2). The importance of these aspects (i.e., emergent phenomena, purpose and extent) is the trade-off between model complexity (e.g. in terms of parametrization) and interpretability; ABM can quickly become so complex that extensive sensitivity and/or uncertainty analyses are necessary to make their results usable, while simpler models must justify their omissions and the corresponding implications for the simulated outputs.
2. *Characteristic elements of ABM* (Fig 1.): Since agriculture is a social-ecological system, the comparison should include the description of the fundamental elements of ABM in this context; the biophysical environment, the socio-economic environment, the agents, and the interactions between agents. The biophysical environment includes all the underlying (spatially explicit) data that determines production in the model such as climate, soil or topographical variables. The socio-economic environment includes prices in markets (exogenous or endogenous) and agricultural policies.
3. *Decision-making elements in a farm systems perspective* (wheels in Fig. 1): We distinguish in this review three dimensions of the decision-making elements: action range, farmers' characteristics and the decision architecture.
    - *Action range* should reflect the multi-output decision context of the farm including non-agricultural activities, land tenure and/or whether household characteristics are considered. Criteria for the action range of the farm were only rated based on whether they were present in a model or not (Table 4).
    - *Farmers' characteristics* describe the ability of the models to distinguish the different farmer- or family-specific individual traits such as *goals, values*, and *emotions*. These criteria reflect the importance of the various socio-psychological and motivational factors that influence farm decision-making, assuming household members share goals values and emotions.

- The *decision architecture* reflect those criteria that have been shown to be of importance in farmers' decision-making and reflect the influence of the family household and its characteristics on the farmers' decision-making beyond income maximization under a short and long-term perspective. It includes *perception, interpretation and evaluation* as a basis for individual learning, *social learning* (from the behaviour and opinions of other relevant actors), *uncertainty in the decision-making process*, the *type of decision-making rule*, *time horizon (annual vs. investment decision)* and consideration of *exit-entry decisions* in the decision-making process as well as the underlying *social interactions* (i.e., agent-agent interactions through social networks and social norms).

The chosen dimensions reflect the standard description of the decision-making process in agent-based models (see last column in Table 1). However, the characteristics of the farmers' decision context (i.e., multi-output decision-making), importance of non-agricultural activities and cultural aspects, as well as the time horizon (annual, investment, entry, exit; i.e., the farm system perspective), are of additional importance. The different elements (i.e., model environment, action range etc.) described in our framework clearly interact, as indicated by the integration of the biophysical and socio-economic environment as a foundation of farmers' decision-making (Fig. 1). Thus, it will not be possible to disentangle these elements and dimensions to a specific functionality in each model.

3.3.2 Assessment of farmers' characteristics and decision architecture in agricultural ABM

To evaluate the representational sophistication in simulating farmers' decision-making we assessed the eleven decision-making elements proposed in the framework for each of the models. Based on the discussion in the workshop and the developers' model description, we classified the implementation of the different review criteria into three levels of representational sophistication (Table 2). After the workshop, the developer of each model reviewed the resulting assessment (Table 5). It is important to note that the rating with respect to different aspects of the decision-making process by no means refers to an assessment of the quality of the models, which is clearly dependent on purpose and research questions in the corresponding study and would go beyond the purpose of this review.

Table 1 Comparison of dimensions to compare decision-making in agricultural systems

			Existing frameworks and classifications of decision-making processes in ABM			
	Dimension	**Criteria used for review**	**MR POTATOHEAD** Parker et al. (2008)	**MoHuB** Schlüter et al. (2017)	**B & G** Balke and Gilbert (2014)	**ODD +D** Müller et al. (2013)
Overview	Purpose	Phenomena addressed	Potential land uses			What key results, outputs or characteristics of the model are emerging from the individuals?
		Purpose of the model				What is the purpose of the study?
	Extent	Spatial extent				What is the spatial resolution and extent of the model?
Characteristic elements of ABM	Agent	Agents	Agent Class			What kinds of entities are in the model?
	Interaction	Interaction	Land exchange class			Are interactions among agents and entities assumed as direct or indirect?
	Biophysical environment	Biophysical environment	Landscape Representation	Biophysical environment		If applicable, how is space included in the model? Do spatial aspects play a role in the decision process?
	Socio-economic environment	Prices / costs / markets	Economic structures	Social environment		What are the exogenous factors/drivers of the model?
		Policies	Institutional/Political constraints			
Decision-making elements in a farm systems perspective	Action range	Agricultural production type	External characteristics	Assets, Perceived behavioural options		What are the subjects and objects of the decision-making? Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?
		Land tenure	Land tenure rules			
		Labour allocation				
		Off-farm work/income				
		Household (characteristics & consumption)				
	Farmers' characteristics	Emotions	Parameters governing decision strategies		Affective	What are the subjects and objects of the decision-making? Do social norms or cultural values play a role in the decision-making process?
		Goals/needs		Goals/needs		
		Values		Values	Norm consideration	
	Decision architecture	Perception, Interpretation, Evaluation	Agent decision model	Perception of bio-physical and social environment		Are the mechanisms by which agents obtain information modelled?
						Is the sensing process erroneous?
				Evaluation		What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Do the agents adapt their behaviour to changing state variables? Is individual learning included in the decision process?
		Social learning	Factors affecting land productivity	Knowledge	Learning	Which data do the agents use to predict future conditions? Is collective learning included in the decision process?
		Uncertainty in decision-making	Attitudes towards risk			To which extent and how is uncertainty included in the agents' decision rules?
		Decision-making rule	Payoffs and decision strategy	Selection	Cognitive	How do agents make their decisions? Are the agents heterogeneous in their decision-making?
		Time horizon: Monthly or annual decisions investement,				Do temporal aspects play a role in the decision process?
		Structural change: Entry and exit decision	Demographic dynamics			

		Social interactions	Non-spatial networks		Social	If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?

Table 2 Review criteria to compare representation of decision-making elements in a farm systems perspective

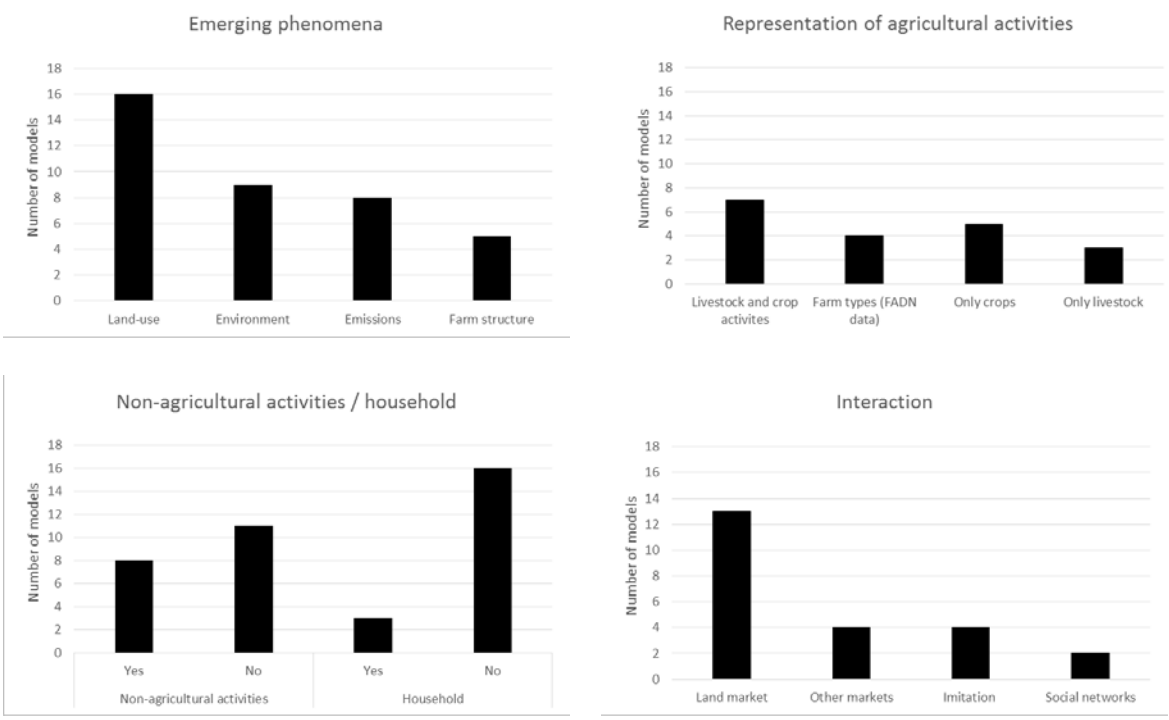
		Levels of representing sophistication in farmers' characteristics and decision-architecture		
Review criteria	**Explanation**	1	2	3
Emotions	Degree of representing emotions in the decision-making process	Not considered	Included as state of agents (e.g. for different activities)	Integrative modelling of emotions in farmers' decision-making
Goals	Consideration of different goals or needs (e.g., financial, social or individual needs) in individual decision-making.	Optimization towards one goal (e.g. income maximization)	Multiple goals with simple prioritization rules (e.g. income maximization with additional objectives in the constraints or lexicographic preferences)	Multiple goals with empirically derived weighting between goals (multi-goal programming)
Values	Deep, slowly changing beliefs, e.g. a conservation value or the value of future benefits (discount rate).	None	Consideration of values as a state variable.	Consideration of values determining preferences / beliefs
Perception, Interpretation, Evaluation	Mechanisms by which agents obtain information, interpret the relationship to their past decisions and how they value this information in their decisions (including individual learning).	Agents are assumed to simply know variables.	Memory of past decisions: Agents change decisions over time as consequence of their experience (socio-economic or biophysical environment).	Explicit representation of the mechanism of how agents perceive and interpret the socio-economic or biophysical environment and how agents change decisions over time as consequence of their experience.
Social learning	Knowledge about the behaviour and opinions of other relevant actors that affects own decision-making.	No memory or knowledge about other behaviour	Agents have knowledge about other agent behaviour and adjust behaviour	Learning i.e., agents change their decisions over time as consequence of their observation of other behaviour.
Uncertainty in decision-making	Consideration of uncertainty/risk in the agents' decision rules.	Not considered i.e., no risk management	Risk management based on simple rules or buffers	Consideration of risk-aware decisions i.e., stochastic dynamic programming.
Decision-making rule	The process by which an individual chooses her behaviour from the set of options.	One rule for all agents i.e., random, optimizing, satisficing	Decision rule based on agent (or agent-type)	Complex structures i.e., two step procedures (e.g. consumat approach)
Time horizon	Temporal aspects in the decision process	Annual decisions only	Annual and investment decisions	Intertemporal decisions i.e., consideration of the optimal point in time of an investment
Structural change	Consideration of family farm cycles such as entry and exit decision, succession probability	Not considered / random	Empirical based exit / entry probabilities	Model endogenous representation of structural change
Social interactions	Effect of social interaction and networks on the agent behaviour.	None	Considering other agent behaviour i.e., imposed network	Emerging interactions based on social networks

4. Results

4.1 Characteristic elements of reviewed ABM

All the models reviewed used farms as their decision-making unit. Four out of the 20 reviewed models included non-farming agents such as institutional or governmental agents (CRAFTY, FEARLUS), nature organizations and estate owners (RULEX) or municipalities and national parks (SERD). A majority of the models addressed spatially explicit land-use changes and the corresponding landscape pattern as an emerging phenomenon (16 out of 20 models). All these models had a spatially explicit representation of the biophysical environment, which varies from synthetic landscapes to high biophysical realism. Fully parameterized models covered, on average, a smaller spatial extent, even though ABMSIM, AGRIPOLIS and MPMAS also cover larger landscapes (i.e., > 500 km^2). Two models (FOM, GLUM) focused only on crop choices without focusing on the aggregation at the landscape level. These two models had a specific, complex representation of the decision-making. SWISSLAND did not reflect spatially explicit land-use patterns due to the non-spatial nature of the underlying data from the Farm Accountancy Data Network (FADN), and in one case modellers addressed manure allocation (Van der Straeten) for which the spatial representation focused on distances rather than land-use patterns. The review also showed that less than half of the models (8/20) considered off-farm income or labour allocation in their simulations. The consideration of non-agricultural activities was via exogenous drivers (e.g. opportunity costs or wages) or derived from FADN. In contrast, only three models also included household consumption in farmers decision-making. In AGRIPOLIS and MPMAS, consumption and savings were again linked to farmers' investment decision.

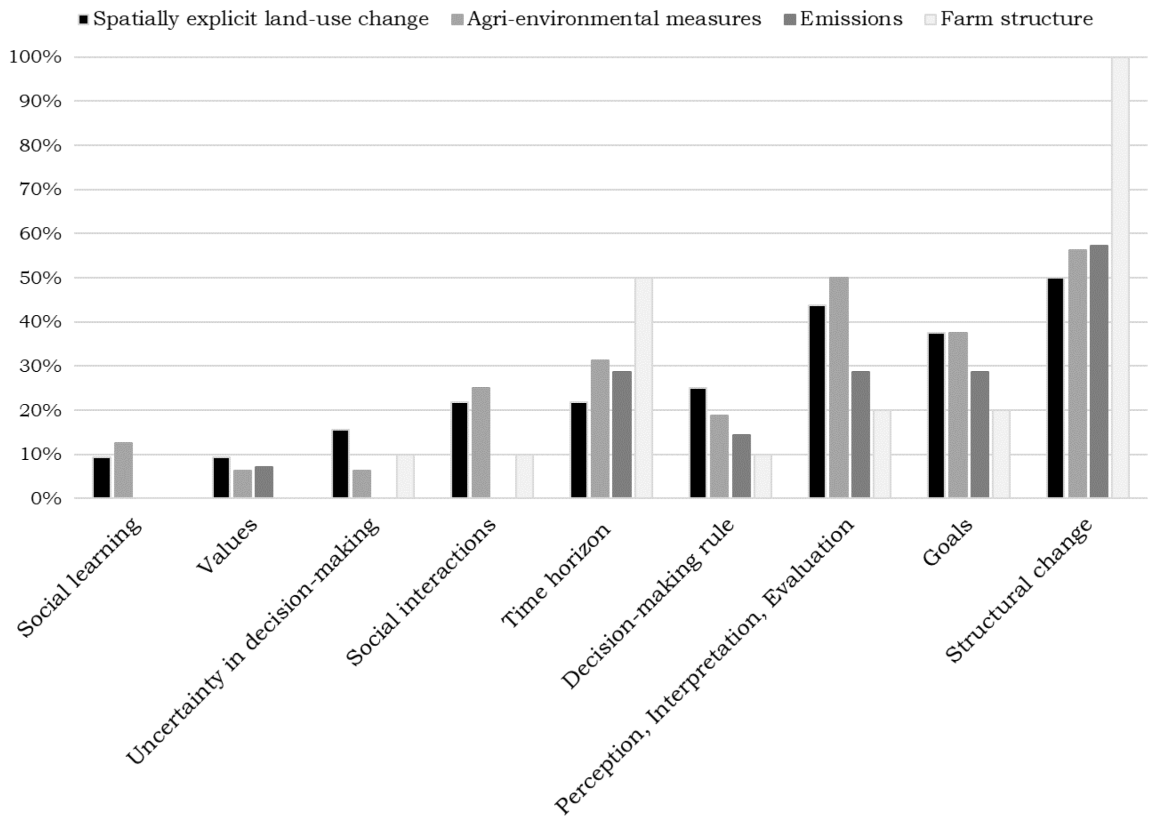
Figure 2. Emerging phenomena, agricultural activities, non-agricultural activities and interactions in European ABM



Note: For emerging phenomena and interactions, models can be counted more than once.

The interaction between farmers in most of the models was based on land markets or another form of land exchange. ABSIM and SERA specifically focused on different types of auction mechanisms in land markets. Not all models using land markets also differentiated between rented and owned land. However, only FEARLUS-SPOMM, in the context of the adoption of biodiversity measures, and SAGA, in the context of the adoption of irrigation technologies, fully addressed social interactions between farmers. In FEARLUS, agents had the ability to check the yields from their neighbours and, based on an aspiration threshold, to either leave land-use unchanged or imitate the land-use choice of its neighbours. In addition, it also considered interactions between farmers and government actors. In the SAGA and the FOM model, social interactions were implemented via the so-called CONSUMAT approach (Jager and Janssen 2012). This approach determined four behavioural strategies, i.e., repetition, optimization, imitation and inquiring based on satisfaction of and uncertainty faced by the farmer. In these models, agents who were uncertain with respect to the benefits of a given farm activity or technology will imitate other agents' activities. Moreover, in SAGA, imitation was mediated through a social network in which a strong link joins peers who had similar farm characteristics and were located nearby. By contrast, in MPMAS, a threshold approach was applied that allowed simulation of different types of adopters such as innovators, early adopters and laggards. The Vista model allowed only for a certain type of farmers (so called absentees) to imitate their neighbours. Finally, CRAFTY also represented social networks that allowed modification of productivity and competitiveness between agents.

Figure 3. Representation of complexity in decision-making elements with respect to emerging phenomena simulated in reviewed ABM



Note: A value of 100% indicates that all models addressing the phenomena have a level of representational sophistication of 3 (in Table 5) for the corresponding review criteria. For example, all models that address farm structures have also a sophisticated representation of family farm cycles, entry and exit decision, or succession probability. A value of 0% implies that if a specific emerging phenomenon is addressed, the corresponding review criteria has a level of representational sophistication of 1 (in Table 5). For example, none of the models that address farm structures represents social learning.

4.2 Decision-making elements in a farm systems perspective

A key advantage of ABM is to consider different goals and values in the farmers' decision-making (13/20). To represent goals, many models used farmer types derived from surveys and/or census data such as hobby-, part-time-, conventional or business oriented farmers. The different agents then varied in their decision-rule (Valbuena, APORIA, CLUM and SPASIM) and/or their parametrization (ALUAM, CLUM, CRAFTY). Two models used decision trees as algorithm for farmers' decision-making representing a lexicographic order of goals (Vista, SERD). These types of models set different decision rules for agents depending on the farmers' and farm characteristics. RPM assumed different "farming styles" as a result of the differences among the farmers in their labour and capital costs and their willingness to support agriculture from other income sources. In RULEX, farmers were differentiated through behaviour types i.e., expanding, shrinking, intensifying or innovating. The model allocated agents to behaviour based on a logistic probability function using farmers' attributes (i.e., age, size etc.) as explanatory variables. In FEARLUS, SAGA, FOM and CRAFTY, heterogeneity in goals could also be determined by varying threshold such as aspiration, tolerance or competition levels.

Beliefs or values were in most case studies considered as part of the farmers' typology. For example, SPASIM used the attitude of the heir to simulate whether a traditional farm had a successor. APORIA, CRAFTY and CLUM used a utility function in which different goals could be weighted to reflect underlying beliefs and values. In the reviewed applications, however, this model functionality was only mentioned as a possibility but not actually used. Thus, there is currently no model that includes endogenous simulation of underlying beliefs to determine preferences or goals in European ABM. Furthermore, emotions are not reflected in any of the reviewed models despite the importance of affective factors described e.g. in Balke and Gilbert (2014).

Risk management and decision-making uncertainty was considered in only a few models (6/20). GLUM used profit maximization and the minimization of risk (i.e., the standard deviation of total income related to expected gross margin) as elements of the farmers' goal function. In MPMAS, penalties for more risky crops could be considered in the objective function. In those models using the CONSUMAT approach, uncertainty was a key variable to determine farmers' behaviour. In SAGA the uncertainty level was defined as the ratio between a farmers' current income and his predicted income, which was derived from their past income using an exponential smoothing algorithm. Similarly, FOM related the farmer's certainty to the average performance within the previous five years (i.e., the farmer was uncertain if their results have been consistently below a minimal satisfaction level). In addition, agents in CRAFTY could have individual variation in give-up and give-in threshold parameters to reflect uncertainties in their decision-making. In SRC, the discount rate used is also determined by the personal risk aversion of the agents. Thus, the consideration of risk management and decision-making uncertainty is currently very limited in European ABM despite its importance in agricultural production decisions.

In many European ABM, farmers were assumed to have perfect knowledge of the value of the variables and they did not have a specific representation of how they obtained information. For example, the proportion of landscape in commercial vs. traditional farming types can influence decisions to change agent type or to exit farming in SPASIM, but it is unclear how individual farmers would come to know this information about the landscape-level state. Specific interactions between the biophysical environment and the agents' behaviour were modelled for the interaction between bird population and farmers land use decisions in APORIA, changes in drought conditions in SAGA, and the level of biodiversity in FEARLUS (mediated through a government agent). This allowed adjusting the farmers' management practice according to the environmental outcome of their past decisions.

In addition, a few models used some form of memory about past decisions, prices or outcomes as a factor in the farmers' decision-making. In Vista, FOM and SAGA, memory of past income was projected into the future and leads to adaption of land-use decisions. In AgriPoliS, agents revised their expectations with respect to output prices periodically by calculating expected prices for land. In SERD, a weighted moving average of the prices in past periods was used to update price information for the farmers. In Valbuena, agent actions like 'cut', 'keep' or 'plant' landscape elements depended on previous choices. Similarly, agents in GLUM accumulated knowledge on crops which increased the possibility that the same crop was chosen (reflecting path dependencies). In APORIA, farmers had a "knowledge base" that contained all the information about land uses and other factors that informed an agent's decision. These approaches allowed the agents to "learn" from past behaviour or outcomes. However, the consideration of feedbacks between farmer networks, collectives or organizations was seldom addressed. Learning through adaptation of behaviour of others was only implemented in SAGA through imitating the adoption and in FEARLUS, in which agents learn by storing new cases i.e., particular land uses.

Thus, the review suggested that models with high sophistication in the representation of perception, interpretation and evaluation (APORIA, SAGA, FEARLUS), goals (APORIA, GLUM), learning (FEARLUS), decision-making rules (VISTA, SAGA, FOM) and social interactions (SAGA, FEARLUS) are generally of the explorative or explanatory type, without a full parameterization of every aspect of the decision-making process. In addition, values and learning, as well as affective aspects of farmers' decision-making, were hardly considered. Moreover, aspects of risk and uncertainty were not often represented in existing models. While many models included some stochastic component to reflect the variability of yields or utilities, this information was not considered within the decision-making rules.

4.3 Decision-making mechanisms and problem domains in agricultural systems

Beside land-use and landscape changes which were considered in most of the models, the emerging phenomena addressed focused on i) farm structural change (5 models), ii) environmental aspects, especially agri-environmental issues (9), and iii) simulation of emissions (8) (see Fig. 2). The phenomena addressed in the models had also implications for the representation of decision-making processes (Fig.3).

First, the group of models that focused on farm structural change had a particularly complex representation of the temporal aspects, including farm entry and exit decisions. The only model that also depicted complex inter-temporal decision-making addressed short rotation coppice allocation (SRC). Thus, the complexity of temporal aspects in the current application of agricultural ABM was clearly driven by the intent to reflect structural change or specific inter-temporal decisions. If this is not specifically addressed, modellers seemed to opt for annual decision-making.

A second group of models addressed the implementation or assessment of policy (especially agri-environmental) measures in the agricultural sector. Here, the complexity of decision-making in the different agricultural ABM varied between incorporating perception, interpretation and evaluation (APORIA, SERA) goals (APORIA, ALUAM), economic performance (AGRIPOLIS, MPMAS, RPM, RULEX, SERA, SWISSLAND) or social interactions (FEARLUS-SOMM). However, the assessment of agri-environmental measures was not reflected in specific properties of the decision-making process.

Third, models focusing on the simulation of environmental impacts such as emissions of nitrogen or greenhouse gases paid attention to detailed representations of farmers' production technology. These models either included both livestock and crop activities or were based on a detailed representation of FADN-derived farm types. As in the case of the agri-environmental policy measures, there was no clear link between the specific problem domain of simulating emissions and any dimension of the decision-making mechanism reflected in our framework.

In summary, the review showed that, depending on the focus of the corresponding ABM, the decision-making process implemented was more or less tailored to characteristics important in a farm systems perspective. The multi-input and multi-output aspects of farming systems were specifically well represented in models addressing emissions from agriculture for which a detailed representation of the production technology is warranted. Models with a specific focus on farm structural change and inter-temporal decisions addressed the temporal context of farmers' decision-making in more detail. Off-farm opportunities and labour allocation were considered in many models but without a specific logic in which context or with respect to a specific phenomenon addressed. Cognitive, affective and social aspects were included in many European agent-based models but with different degrees of representational sophistication and addressing no shared problem domain.

Table 3 Characteristic elements of agricultural agent-based models in European case studies

Model (key reference)	Emerging phenomena	Purpose	Spatial & temporal extent	Agent	Interaction	Biophysical environment	Socio-economic environment	
							Prices and costs	Policies
ABMSIM Britz und Wieck (2014)	Spatially explicit land-use, farm structures	A	1300 km² 30 years	Individual farms, aggregate land-use agent	Land market, market for rights (milk delivery, manure disposal)	Spatially explicit (slope, elevation, soil)	Exogenous	Decoupled payments, environmental standards
AGRIPOLIS Happe et al. (2011)	Structural change (farm structures, land-use, production) and land prices	A	200 - 1700 km² 15 years	Individual farms	Land markets, product markets	Synthetic landscape	Exogenous (in some regions markets using Tâtonnement process)	EU-CAP
ALUAM Brändle et al. (2015)	Land-use and land cover change in mountain regions under global change	A	120 km² 20 years	Farm types i.e., group of farmers with similar production and decision-making	Land market	Spatially explicit (soil, slope, distance to farm etc.)	Exogenous	Full representation of Swiss AgPolicies
APORIA Guillem et al. (2015)	Land-use, farm structures	B	132 km² 50 years	Land manager	Land market	Spatially explicit (biophysical properties)	Exogenous	Activity based subsidies or restrictions
CRAFTY Brown et al. (2016b)	Land-use change at European scale	B	1600 km² 30 years	Land manager, institutional agents	Land markets, institutions influence agents' characteristics	Spatially explicit (distances, productivity)	Based on supply (endogenous) and demand (exogenous)	Institutions implement types of polices (subsidies, protection)
FEARLUS-SPOMM Polhill et al. (2013)	Species diversity, farm business viability	C	- 80 years	Land management agent and government agent	Giving advice, species occupancy	All land equally suitable	Exogenous	Four different payment schemes
FOM Malawska and Topping (2016)	Crop allocation and farm profit	C	100 km² temporal unrestricted	Farmer types (profit maximizer, yield maximizer, environmentally-oriented farmer)	Neighbour imitation	Spatially explicit	Exogenous	-
GLUM Holtz and Pahl-Wostl (2012)	Transition from rainfed to irrigated agriculture	B	16'000km² retrospective (1960-2010)	Farm types (part-time, family farm, business oriented)	Observing other agents' activities	-	Exogenous (no prediction)	Relevant CAP policies
MPMAS Troost et al. (2015)	Regional agricultural supply, land-use, farm structures, participation in agri-environmental schemes	A	1300 km² 10 years	Farming households (full-time farms)	Land market	Spatially explicit (soil classes, distance to farm)	Exogenous	EU CAP, agri-environmental schemes, Renewable Energy Act (EEG)
RPM Roeder et al. (2010)	Agricultural production. area of protected habitats	A	2.5 km² 30 years	Individual farms	Land market	Spatially explicit (vegetation, topography)	Exogenous	Relevant payment schemes
RULEX	Land markets, spatially explicit land use change, rural depopulation, farm	A	300 km²	Land owners: individual farmers (subdivided in categories), individual	Agents buy and sell land from/to each other.	Climate change affects hydrological soil properties	Exogenous	Policies for implementing national ecological network

Bakker et al. (2015)	size growth, intensification.		retrospective (2001-2009)	estate owners, and nature conservation organizations				
SAGA van Duinen et al. (2016)	Adoption rates of irrigation technology, water demand, agricultural production	B	138 km² 30 years	Individual farms	Social interactions	Spatially explicit (belonging to island, access to water)	Input prices are set exogenously, crop prices are modelled endogenously but remain constant	-
SERA Schouten et al. (2013)	Land use patterns	B	606 km² 25 years	Dairy farm households (traders) and auctioneer	Land market	Spatially explicit (land quality, distances)	Exogenous	Agri-environmental schemes
SERD Gaube et al. (2009)	Land-use change, N and carbon flows	B	20 km² 30 years	Individual farmers, aggregated household, administration, enterprises, tourists	Land market	Spatially explicit	Exogenous	EU subsidies
SPASIM Millington et al. (2008)	Spatially-explicit land use (and land cover when integrated with landscape fire succession component)	C	9.2 km² 50 years	Farmers (two types: 'commercial' and 'traditional')	Land market	Spatially explicit ('land capability', distance to road, initial land use/cover)	Exogenous	-
SRC Schulze et al. (2016)	Expansion of short rotation coppices (SRCs)	B	1125 km² 50 years	Land users	Indirectly via the endogenous market	Spatially explicit (soil qualities)	Market price is given by external demand, supply is endogenously generated	-
SWISSLAND Zimmermann et al. (2015)	Land-use, farm structures and production, N-flows	A	55'000 farms 15 years	FADN farms	Land market	-	Costs are exogenous parameters; product prices based on partial equilibrium demand module	Full representation of Swiss AgPolicies
Valbuena Valbuena et al. (2010)	Landscape structure of a Dutch rural region	A	600km² 15 years	Farm type (hobby, conventional, diversifier, expansionist)	Land market	Spatially explicit (size, productivity)	Exogenous	-
Van der Straeten Van der Straeten et al. (2010)	Manure disposal	B	60'000 Flemish farms -	Farms, transport firm agent	Manure transport market	-	-	Processing obligation
VISTA Acosta et al. (2014)	Simulation of traditional agricultural landscape	A	44 km² 50 years	Individual farmers, in typology groups (innovative, active, absentee, and retiree)	Land market, neighbour imitation	Spatially explicit (agricultural suitability)	Exogenous	CAP payments

*Purpose of modelling: A Explanatory with full empirical parameterization; B Explanatory with empirical context, but abstracted parameterization; C Explorative with theoretical motivation and partial parameterization

Table 4. Action range in agricultural agent-based models in European case studies

Model	Representation of the action range in agricultural ABM			
	Production type	Land tenure	Off-farm	Household
ABMSIM	All farm types (arable, dairy, pigs, mixed, biogas)	Ownership and rental considered	Off-farm wages and labour considered	-
AGRIPOLIS	Livestock, crops	Ownership and rental considered (random length of contract)	Derived from accountancy data	Maximization of household income
ALUAM	Livestock and crops	Land belongs to farm agent types (no renting)	Considered as opportunity costs of production and labour restrictions	-
APORIA	Crops	Parcel ownership considered	-	-
CRAFTY	Livestock, crops	Land belongs to farm agent types (no renting)	-	-
FEARLUS-SPOMM	Crop type and intensity	Land belongs to farm business (no renting)	-	-
FOM	Livestock, crops	-	-	-
GLUM	Crops	-	Restrictions per farm type	-
MPMAS (Germany)	Livestock, crops, biogas	Ownership and rental considered	Off-farm considered only for successor	Provides labour, determines successor, consumption, and demographics
Vander Straeten	Manure type (cattle, pigs, poultry and other)	-	-	-
RPM	Livestock	Ownership and rental considered	-	Consumption considered
RULEX	FADN farm types	Differences between owners or tenants are ignored: everybody is a user with full mandate	-	-
SAGA	Crop production	-	-	-
SERA	Livestock	Ownership and rental considered	-	-
SERD	Livestock, grassland, forest	Land tenure considered	Empirically compiled	-
SPASIM	Arable, pasture	Land belongs to farm agent (no renting)	-	-
SRC	No cultivation, crops for food or feed, SRC	-	-	-
SWISSLAND	All farm types (arable, livestock, mixed etc.) occurring in the FADN farm sample	Farmers can lease land	Derived from FADN	Maximization of household income.
Valbuena	All farm types	Parcel ownership considered	-	-
VISTA	Livestock, crops	Ownership and rental considered	Off-farm wages and labour considered	-

Table 5 Representation of complexity of decision-making elements in agricultural agent-based models in European case studies

	Purpose (see Table 3)	Social learning	Values	Uncertainty in decision-making	Social interactions	Time horizon	Decision-making rule	Perception, Interpretation, Evaluation	Goals	Structural change
ABSIM	A	1	1	1	1	2	1	1	1	3
AGRIPOLIS	A	1	1	1	1	2	1	2	1	3
ALUAM	A	1	1	1	1	2	1	1	2	2
MPMAS	A	1	1	2	2	3	1	2	2	3
RPM	A	1	1	1	1	2	2	1	1	3
RULEX	A	1	1	1	1	1	2	1	2	3
SWISSLAND	A	1	1	1	1	2	1	1	1	3
Valbuena	A	1	1	1	1	1	1	2	2	2
VISTA	A	1	1	1	2	1	2	2	2	3
APORIA	B	1	2	1	1	1	2	3	3	1
CRAFTY	B	1	2	2	2	1	1	2	2	1
GLUM	B	1	2	3	1	2	2	2	3	1
SAGA	B	2	1	3	3	1	3	3	2	1
SERA	B	1	1	1	1	1	1	2	1	1
SERD	B	1	1	1	1	1	2	2	2	2
SRC	B	1	1	2	1	2	1	1	1	1
Van der Straeten	B	1	1	1	1	1	1	1	1	1
FEARLUS	C	3	1	1	3	1	1	3	2	1
FOM	C	1	1	2	2	1	3	1	2	1
SPASIM	C	1	2	1	1	1	2	2	2	2
Total score		**23**	**24**	**28**	**28**	**29**	**31**	**35**	**35**	**38**
Average group A models		1.0	1.0	1.1	1.2	1.8	1.3	1.4	1.6	2.8
Average group B models		1.1	1.4	1.8	1.4	1.3	1.6	2.0	1.9	1.1
Average group C models		1.7	1.3	1.3	2.0	1.0	2.0	2.0	2.0	1.3

5. Discussion

Agent-based modelling approaches in the European agricultural sector potentially have many advantages. In particular, the "bottom up" approach, through considering heterogeneity in decision-making and representing spatial and social interactions, complements other scientific policy evaluation tools such as integrated assessment tools (van Ittersum et al., 2008), (partial) equilibrium models (Schroeder et al., 2015), economic experiments (Colen et al., 2016) or econometric approaches (Imbens and Wooldridge, 2009).

However, are existing ABM equipped with the properties and behavioural functions capable of generating reliable and robust simulations? It is clear that the properties to be considered in a model depend on the purpose of the study. Increasing complexity in representations of farmers' decision-making may not necessarily be useful or even meaningful (Sun et al., 2016). Thus, this review does not explicitly judge the quality of each model but tries to describe the current state of research as a whole, and to scrutinize whether particular agent decision-making formulations are more appropriate for some particular decision-making situations rather than others (Parker et al., 2003).

5.1 Specific properties of farm systems important in modelling farmers' behaviour in ABM

Based on a farm systems perspective (see e.g. Jones et al., 2016), we argue that the multi-output nature of production, the coexistence of agricultural and non-agricultural activities, the heterogeneity of household and family characteristics and the concurrence of short and long-term decisions are important properties of farmers' decision-making. Our proposed framework to describe agricultural ABM is rooted in the categories of existing frameworks (Parker et al., 2008), classifications (Schlüter et al., 2017; Balke and Gilbert 2014) and the ODD+D standard protocols to describe decision-making in ABM (Müller et al., 2013). The added value is that it concretises and complements existing elements of describing agricultural ABM from a farm systems perspective. Thus, the framework could be extended for use in describing farmers' decision-making in several contexts and shed light on the agent-based modelling of agricultural systems in other parts of the world. We add to recent reviews of decision-making in ABM (e.g. An, 2012; Groeneveld et al., 2017, Kremmydas et al., 2018), by focussing on models that address agricultural policy aspects in the context of European "multifunctional" agriculture and show that the dimensions and elements presented help to categorize and compare decision-making processes in ABM.

5.2 Types of decision-making mechanisms in European ABM

Existing empirical research suggests that farmers' decision-making is strongly influenced by individual values, attitudes and preferences (e.g. Benjamin and Kimhi, 2006; Burton and Wilson 2006; Weltin et al., 2017) and farmers' interactions through networks (Moschitz et al., 2015; Schneider et al., 2012; Sol et al., 2013). This implies that reliable and robust models of agricultural systems could profit from more modelling effort in differentiating farmers' decision-making according to their individual and social characteristics. Therefore, there seems to be considerable potential for European ABM to increase the sophistication in representing farmers' decision-making mechanisms and interactions with each other.

Our review implies that current ABM applied to European agriculture address farmers' decision-making processes on various levels of sophistication depending on the purpose of the model and the corresponding research questions. We find models to be sophisticated in the representation of farm exit and entry decisions, as well as the representation of long-term decisions and the consideration of farming styles or types using farm typologies. Perceptions, Interpretation and evaluation also occur in many models. There are considerably fewer attempts to model farmers' emotions, values, learning, risk and social interactions in the different case studies. In addition, non-agricultural activities and household-level decisions are also rarely considered in European agricultural ABM, despite their relevance (Meraner et al., 2015; Weltin et al., 2017).

The scarcity of attempts to model aspects such as values or social interactions is somewhat in contrast to ABM in other regions and farming systems. For example, in the context of social interactions and neighbourhood effects and their influence on farmers' behaviour there exist various empirical and theoretical agent-based models (e.g. Bell et al., 2016; Caillault et al., 2013; Chen et al., 2012; Manson et al., 2016; Rasch et al., 2016; Sun and Müller, 2013). Also, with respect to decision-making rules, there seems to be greater variety outside the European context (Acevedo et al., 2008; Berger et al., 2017; Janssen and Baggio, 2016; Le et al., 2008; Le et al., 2012; Manson and Evans, 2007; Matthews, 2006; Rebaudo and Dangles, 2011; Schreinemachers and Berger, 2011). In a developing country context, the MPMAS model has recently been applied to the assessment of collective action of coffee farmers in Uganda (Latynskiy and Berger, 2017). Looking beyond the agricultural sector, the scope for increasing complexity in the representation of farmers' decision-making is even broader, as the reviews by Balke and Gilbert (2014) and Utomo et al. (2018) show.

5.3 Representation of farm behavioural in specific problem domains

ABM in the European context focus on land-use and land-use changes on various spatial and temporal levels. Land markets represent the key mechanism representing farmers' interactions in almost all of the reviewed models. We did not, however, find any pattern with respect to the spatial extent used in the application of the models. Explanatory models with empirical parameterization usually have a shorter temporal extent compared to more abstract or theoretical motivated models.

Models focusing on farm structural change have a particularly complex representation of the temporal aspects, as well as farm entry and exit decisions. The simulation of environmental aspects such as nitrogen or greenhouse gas emissions provide a detailed representation of the farmers' production technology and thus are usually more sophisticated with respect to the multi-output nature of production.

Models that address the implementation of agri-environmental measures or the assessment of landscape changes in the agricultural sector do not seem to focus on specific domains or properties of farmers' decision-making process. Off-farm opportunities and labour allocation are considered in many models but without addressing a specific phenomenon. Complex representations of decision-making with respect to cognitive or social aspects are currently not, or only partly, implemented in explanatory models with full empirical parameterization.

This suggests that there are trade-offs between a complex representation of farmers' decision-making and the detailed representation of multi-output production systems, non-farm opportunities and complex long-term decisions of European farms with full parameterization. Thus, there is considerable potential for the reuse of parameters, modules or code within this research community, as postulated by several scholars (Bell et al., 2015; Schulze et al., 2017). This can be especially fruitful for agricultural ABM since they often focus on specific aspects of decision-making but are applied to the same emerging phenomenon (e.g. in the context of agri-environmental measures). This practice would not only save modelling and validation efforts, but also increase the replicability of the studies using the model. Meanwhile, it indicates opportunities to improve the representation of farmers' decision-making in European ABM.

5.4 Challenges and prospects of agricultural ABM

Challenges and prospects for agricultural ABM were also critically discussed in the workshop. There was a consensus that increasing diversity in decision-making and the integration of social interactions in agricultural ABM is of crucial importance to model emerging phenomena in agricultural systems. The increase in representational sophistication could even be used to address additional aspects such as the consideration of entrepreneurship, strategic decision-making or interactions along the value chain.

To increase the realism of the representation of agricultural system and the use of ABM in policy assessment, there seems to be an opportunity to align the above mentioned two streams of literature: Those models that include multi-output production systems, non-farm opportunities and complex long-term decisions and those models addressing more complex representations of decision-making considering also values, risk, learning and social interactions. To this end, the production of more generalizable results in the various models could inform one another and collectively build up a picture of major behavioural processes in farm systems. This would offer the opportunity to make an informed decision on where to account for specific dimensions or elements of the decision-making process to improve representation of the way people act. This could support the future development of better models to support agricultural policy making by investigating what is important and what works for which question or farming system. To lay the ground for such multi-model inter-comparison, a first step could be to use models that address the same emerging phenomena in the same case study to allow for a specific evaluation of the different model characteristics. This would allow direct identification of the relevant properties and behavioural patterns of the farmer representation that might increase the reliability and robustness of simulations.

There are, however, some well-known challenges with the aspiration to represent real systems in an adequate manner and at the same time increase the sophistication of the decision-making process. These challenges apply to ABM also beyond the European context. First, the difficulties of parameter calibration and proof of validity increases with model complicatedness, i.e. the challenge of parsimonious system presentation. Empirical ABM have been criticized for their large data requirements and high uncertainty of input parameters (Magliocca et al., 2015; O'Sullivan et al., 2015; Troost and Berger, 2015). While ignoring highly uncertain processes may give illusory certainty in other modelling approaches, the communication and applicability of ABM in ex-post and ex-ante evaluations of agricultural policies are still crucial challenges.

Second, there is a danger of creating ‘integronsters’ that are difficult to understand and become a black box for stakeholders and users (Bell et al., 2015; Voinov and Shugart, 2013). Third, the communication of the model may become more challenging, especially if models will be used in policy evaluations that also need a comprehensive description of the model for non-scientists (Müller et al., 2014). Fourth, “mid-level” models between simple (often theoretical) and complex models may create new risks such as over-specification or unnecessary complexity (Sun et al., 2016). Thus, the increase of sophistication in representing decision-making processes may intensify these challenges of calibrating, validating and communicating agricultural ABM.

Existing literature suggests that there are various approaches to tackle these challenges, with a broad stream of literature on do’s and don’ts in designing ABM which should be considered in the development, as well as in sharing and comparing of these models (Abdou et al., 2012; Helbing, 2012; Macal and North, 2010; Smajgl and Barreteau, 2014). Using careful software engineering techniques is an essential pillar in this context. More importantly, aligning a proper representation of agricultural systems with complex decision-making in ABM must include careful sensitivity analysis and model verification including a thorough and transparent unit-testing (Le et al., 2012; Lee et al., 2015; Ligmann-Zielinska, 2013; O’Sullivan et al., 2016; Troost and Berger, 2015). Machine learning and the development of surrogate meta-models can help to efficiently explore parameter space and effectively improve calibration exercises (Lee et al., 2015; Pereda et al., 2017). In addition, pattern-oriented modelling is an approach to avoid making an ABM become over-parameterized and lose predictive power (Grimm and Railsback, 2012; Grimm et al., 2005). Moreover models should be as transparent as possible (e.g. by using ontologies in the computer science sense of a formal representation of conceptualisation (Livet et al., 2008; Polhill and Gotts, 2009)), or by using standard protocol ODD+D (Müller et al., 2013, Kremmydas et al., 2018) or model design patterns (Parker et al., 2008). Various authors also suggest increasing the reuse and sharing of model modules, codes or sub-models, through open-source development for example OpenABM.org (Bell et al., 2015; Schulze et al., 2017). Hybrid models that tightly integrate or combine two or more approaches could be a promising direction in this context (O'Sullivan et al., 2016). The give-and-take exercise at the workshop showed that the model developers and experts in farmers' decision-making are keen to share knowledge, data and model codes (Appendix C, Fig. 3).

Furthermore, some authors suggest that modellers should search for and engage with other (social) scientists studying decision-making (Meyfroidt, 2013; Schulze et al., 2017). This could improve plausibility of models with regard to farmers' behaviour from a psychological point of view (Schaat et al., 2017). The Venn diagram exercise during the workshop (Appendix C, Fig. 1) implied that the goal of most of the agricultural agent-based modellers in Europe is to better reconcile empirical data and theoretical foundations including other modelling approaches, or at least to attentively monitor developments in the other fields. Also here, the Give-and-Take matrix showed that there would be actually many practical opportunities for collaboration between experts on decision-making and agent-based modellers. Agent-based modellers should thus proactively consider opportunities to work together on model comparison and integration in research collaborations.

The discussions at the workshop resulting from the toolbox approach confirmed prospects and bottlenecks in the process towards better reuse, model inter-comparison, hybrid modelling and model ensembles. Data availability, reliability and the fact that models are usually built for different cases are seen as critical challenges (see Appendix C, Fig. 2). Particularly, data collection with respect to interactions (e.g. among farmers) is challenging. Here, new data sets such as those collected with the help of mobile phone apps could be of added value (Bell, 2017). Finally, the validation of the models, or at least of parts of the models, and their trustworthiness remains a major challenge for robust and reliable modelling (O'Sullivan et al., 2016; Polhill et al., 2016). Experts at the workshop, however, were also convinced that ABM is a powerful tool to explore and understand potential decision-making, and so complement social science and other disciplines, rather than simply adopting findings in calibration. In addition, the view was that ABM form an ideal vehicle to integrate social sciences also with natural sciences, something that is urgently needed if we want to address today's most pressing environmental problems.

6. Conclusion

For reliable and robust ABM that allow for the assessment or evaluation of policy instruments, a realistic representation of the farmer's decision context is crucial. This is of specific importance in the European context where the CAP substantially shape the landscape of farm systems via affecting farmers' decision-making. We reviewed 20 European agricultural ABM with a focus on the representation of the decision-making process. The results showed that, depending on the focus of the corresponding ABM, the decision-making process includes different elements that we consider to be important from a farm systems perspective. The lack of consideration of many values, social interactions, norm consideration, and learning in farmers' decision-making across European agent-based models leaves considerable room to improve the representation of farmers' decision-making and a better representation of an agricultural systems perspective in ABM. This presents an opportunity to align the simulation of farmer's decisions more closely to actual decisions. Our hope is that this view supports the dialogue not only between developers of agricultural ABM but also the broader community of agricultural systems modellers and data-driven social sciences. This could fertilize more coordinated and purposeful combinations of ABM and other modelling and empirical approaches in the agricultural sector beyond the European perspective. This is ultimately the key to developing reliable explanatory models of agricultural systems and their use in ex-ante or ex-post agricultural policy evaluations.

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