

1Representation of decision-making in European agricultural agent-based models

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31Highlights

32•Agent-based modelling is a suitable tool for improving the understanding of farmers' behaviour.

33•Review 20 agricultural ABM addressing heterogeneous decision-making processes in the context of Euro-

34pean agriculture.

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35•Considerable scope to improve diversity in representation of decision-making by combining existing mod-
36elling approaches.

37•More coordinated and purposeful combinations of ABM and hybrid modelling approaches are needed.

38•Results provide an entry point for collaboration of agent-based modellers, agricultural systems modellers
39and social scientist.

40Abstract

41The use of agent-based modelling approaches in ex-post and ex-ante evaluations of agricultural policies has
42been progressively increasing over the last few years. There are now a sufficient number of models that it is
43worth taking stock of the way these models have been developed. Here, we review 20 agricultural agent-
44based models (ABM) addressing heterogeneous decision-making processes in the context of European
45agriculture. The goals of this review were to i) develop a framework describing aspects of farmers' decision-
46making that are relevant from a farm-systems perspective, ii) reveal the current state-of-the-art in
47representing farmers' decision-making in the European agricultural sector, and iii) provide a critical
48reflection of underdeveloped research areas and on future opportunities in modelling decision-making. To
49compare different approaches in modelling farmers' behaviour, we focused on the European agricultural
50sector, which presents a specific character with its family farms, its single market and the common
51agricultural policy (CAP). We identified several key properties of farmers' decision-making: the multi-output
52nature of production; the importance of non-agricultural activities; heterogeneous household and family
53characteristics; and the need for concurrent short- and long-term decision-making. These properties were
54then used to define levels and types of decision-making mechanisms to structure a literature review. We
55find most models are sophisticated in the representation of farm exit and entry decisions, as well as the
56representation of long-term decisions and the consideration of farming styles or types using farm
57typologies. Considerably fewer attempts to model farmers' emotions, values, learning, risk and uncertainty
58or social interactions occur in the different case studies. We conclude that there is considerable scope to
59improve diversity in representation of decision-making and the integration of social interactions in
60agricultural agent-based modelling approaches by combining existing modelling approaches and promoting
61model inter-comparisons. Thus, this review provides a valuable entry point for agent-based modellers,
62agricultural systems modellers and data driven social scientists for the re-use and sharing of model
63components, code and data. An intensified dialogue could fertilize more coordinated and purposeful
64combinations and comparisons of ABM and other modelling approaches as well as better reconciliation of
65empirical data and theoretical foundations, which ultimately are key to developing improved models of
66agricultural systems.

67

68 1. Introduction

69Governments strongly influence and support the agricultural sector in Europe and there is increasing interest in a
70critical evaluation of these policies (EU 2015). In this context, reliable explanatory models of agricultural systems
71are of key importance since they allow evaluations of effectiveness and efficiency of policy measures where
72empirical data is not (yet) available e.g. in climate change impact studies, modelling counterfactual scenarios of

73policy changes, or future market conditions. Understanding how farmers take decisions, including anticipation
74strategies, adaptive behaviour, and social interactions is crucial to develop such models (Janssen and Ostrom,
752006; Meyfroidt, 2013, Berger and Troost, 2014).

76In recent years, agent-based models (ABM) have gained increasing popularity for modelling agricultural systems
77and the impacts of policies (e.g. Nolan et al. 2009, Groeneveld et al. 2017, Kremmydas et al., 2018). Agent-based
78modelling represents a process-based "bottom-up" approach that attempts to represent the behaviours and
79interactions among autonomous agents through which agricultural systems are evolving and thus to simulate
80emergent phenomena without having to make *a priori* assumptions regarding the aggregate system properties
81(Brown et al., 2016a; Helbing, 2012; Magliocca et al., 2015). Thus, agent-based modelling is a suitable tool for
82improving the understanding of farmers' behaviour in response to changing environmental, economic, or
83institutional conditions, particularly on the local level (An, 2012; Magliocca et al., 2015).

84Agent-based modellers often choose to build new models from scratch (O'Sullivan et al., 2016) and take varying
85approaches, from microeconomic models to empirical and heuristic rules (An 2012, Schlüter et al. 2017), based on
86whichever suits their purposes best. As a consequence, empirical data on farm decision-making collected for
87model building is often specific to one model, one geographic region, and the particular processes being
88represented. The key challenge is to ensure that, for sake of parsimony, the representation of decision-making in
89agricultural ABM is equipped with those properties and behavioural patterns of the farmer that are relevant for a
90given purpose, and no more or less (Balke and Gilbert, 2014).

91The representation of farmers' decision-making crucially depends on the phenomena to be simulated and the
92purpose of the study. Modellers may abstract or ignore system properties in a specific modelling endeavour even
93though the corresponding mechanism is important from a conceptual perspective. Because no single approach is
94best suited to represent decision-making in general, comparing different research efforts can help to identify
95which particular agent decision-making representations are appropriate for particular model purposes (Parker et
96al. 2003). This could support more coordinated and purposeful combinations of ABM and other hybrid modelling
97approaches in the agricultural sector, which would lead to improved models of agricultural systems (O'Sullivan et
98al., 2016).

99Model comparisons and reviews are frequent in land-use and land-cover ABM (Parker et al., 2008a; Parker et al.,
1002008b) and recently more generic and flexible modelling approaches such as agent functional types (Arneth et al.,
1012014; Murray-Rust et al., 2014a) or agent-based virtual laboratories (Magliocca et al., 2014) have emerged. While
102these comparisons and reviews are very useful, they do not provide an in-depth analysis of specific models and its
103functionalities. Notably, a proper analysis and comparison of agents' decision-making in agricultural ABM with a

104specific focus on European agriculture and its specific policy context is lacking. The European agricultural sector
105with its single market and its common agricultural policy (CAP), fundamentally anchored in the concept of
106multifunctionality, provides a specific setting of economic and institutional conditions that allows for a meaningful
107comparison of different approaches in modelling farmers' behaviour. This setting is particularly distinct from that
108of subsistence farming in developing countries or very large farms in the US or Australia. With many researchers
109currently engaged in agricultural ABM in Europe, there seems to be a fruitful basis for more in-depth comparison
110of models within the same research domain and research focus.

111Thus, here we reviewed existing ABM in the European agriculture context with a specific focus on the
112implementation of the farmers' decision-making process. The research questions are:

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

118The review provides a first entry point for agent-based modellers, the broader community of agricultural systems
119modellers and data-driven social scientist for the re-use and sharing of model components and codes as well as
120for the identification of meaningful model comparisons in the context of farm systems analysis. This is the key to
121develop comprehensive models of agricultural systems and their use in ex-ante or ex-post agricultural policy
122evaluations. The paper is structured as follows. In a background section, we summarize existing reviews on
123decision-making in ABM and outline a farm-systems perspective on decision-making in agricultural ABM. We then
124describe the review process and the levels and decision types used for the description of the models. In the
125Results section, we illustrate how the conceptualisation of decision-making varies by research question in
126agricultural ABM. Finally, we discuss our results with respect to ABM in general and outline future prospects for
127decision-making in agricultural ABM.

128 **2. Conceptual background**

129 *2.1 Description of decision-making in ABM*

130Several recent reviews have classified the types of decision-making used in ABM in social-ecological or human-
131nature systems, either from an operational or a theoretical perspective. In his review, An (2012) classified the
132different theoretical approaches into nine decision models, ranging from microeconomic mechanisms to
133psychological and cognitive models. The ODD protocol is currently the standard for describing ABM, with a

134specific extension for human decisions ODD+D (Müller et al., 2013). The ODD protocol is structured in three basic
135elements i.e., overview, design concepts and details (Grimm et al., 2006; Grimm et al., 2010). According to ODD+D,
136the individual decision-making should be described by making explicit the subjects and objects of decisions, the
137levels of decision-making, rationality/objectives, decision rules and adaption, social norms and cultural values,
138spatial aspects, temporal aspects, and uncertainty. The protocol has already been used to compare different ABM
139land-use models (Groeneveld et al., 2017; Polhill et al., 2008) and agricultural ABM (Kremmydas, et al., 2018). The
140MR POTATOHEAD¹ framework has also been used to compare agent-based land-use models (Parker et al., 2008).
141The framework distinguishes six conceptual classes; information/data, interfaces to other models, demographic,
142land-use decision, land exchange, and model operation. Compared to the more general ODD, MR POTATOHEAD
143enables a more detailed comparison of *land-use* related ABM.

144With a stronger focus on theoretical aspects of the decision-making, the MoHuB (Modelling Human Behaviour)
145framework provides a tool for mapping and comparing behavioural theories of individual decision-making of a
146natural resource user (Schlüter et al., 2017). MoHuB distinguishes between the individual and its social and
147biophysical environment, which interact through 'perception' of the environment and agents' 'behaviour'. The
148actual 'selection' process of behaviour depends on the 'state' of the agent, which includes its goals, values,
149knowledge and assets as well as its 'perceived behavioural options'. The 'evaluation' of the consequences of an
150agent's behaviour on its 'state' closes the loop. The authors use this framework to describe different theories,
151including the concepts of *Homo economicus*, bounded rationality, theory of planned behaviour, reinforcement
152learning, descriptive norms, and prospect theory (see Schlüter et al., 2017). Balke and Gilbert (2014) focus on the
153decision-making process within ABM, but not restricted to land-use or social-ecological systems. Their review is
154itself based on other classifications and reviews (i.e. on Helbing, 2012; Meyer et al., 2009; Tesfatsion and Judd,
1552006), and identifies cognitive, affective, social and norm consideration and learning as the key dimensions in
156describing and comparing human decision-making in ABM. A similar classification can also be found in Kennedy
157(2012).

158In general, all of these classifications and frameworks can be used to compare the representation of decision-
159making in European agricultural ABM. Many of these frameworks, however, use different classes for describing
160similar aspects of the decision-making depending on their purpose (i.e., whether they offer practical guidelines to
161build, describe or compare ABM). In this study, we combined elements of the different frameworks in order to
162address the specific challenges of understanding (i) farm decision-making, (ii) its representation within ABM, (iii)
163and their use in the context of European agricultural systems (see Method section).

91 MR POTATOHEAD: Model representing potential objects that appear in the ontology of human environmental
10actions and decisions

165The major advantage of ABM is their ability to consider heterogeneous agents and their interactions, along with
166feedbacks to simulate emergent properties of a system (Matthews et al. 2007). Thereby, ABM allow the
167representation of agent-specific behaviour covering individual preferences or motivations (e.g. An, 2012; Bruch
168and Atwell, 2015; Kelly et al., 2013). This is particularly relevant in the agricultural sector in which farming families
169are the main decision makers but differ widely, and whose decision-making often goes beyond income
170maximization (Feola and Binder, 2010; Meyfroidt, 2013, Levine et al. 2015, Howley 2015). For many farmers, for
171example, farming is a vocation that is valued in itself and goals such as maintaining farming lifestyle, upkeep
172traditions or fulfilment of personal 'intrinsic' values i.e., enjoyment of works tasks or enjoyment of self-
173employment may be as important as economic drivers (Burton and Wilson, 2006; Gasson, 1973; Howley et al.,
1742017; Howley et al., 2014).

175Recent publications in the context of social-ecological systems modelling (Filatova et al., 2013, Schulze et al.
1762017), integrated assessment (Laniak et al., 2013), agricultural systems modelling (Jones et al., 2016) and policy
177impact assessments (Reidsma et al. 2018) suggest that there is a need for improved representation of farmers'
178heterogeneous decision-making. The representation should not only consider cognitive individual processes,
179personal characteristic, or social interactions (as in most non-agricultural ABM), but also the socio-economic and
180natural environment as well as farm household characteristics. This has four important implications that
181distinguish decision-making in farm systems from other agents typically represented in agent-based modelling.

182First, decisions at the farm level are based on a multi-input and multi-output production functions (e.g. Ciaian et
183al., 2013; Shrestha et al., 2016). For example, farms often include crop and livestock production activities, which
184are linked via manure or fodder balances. Thus, resources such as land, labour and capital must be allocated to
185different marketed and non-marketed products, with a high degree of uncertainty and risk stemming from markets
186or production conditions (Hardaker et al. 2015). As a consequence, technological and economic
187interdependencies (Abler, 2004) and risks and uncertainties play a crucial role in the agents' decision-making
188(Jager and Janssen, 2012).

189Second, farmers' decisions are also often affected by non-agricultural activities (Rossing et al. 2007). For example,
190most family farms represent both a household and a business unit at the same time (Evans, 2009; Graeub et al.,
1912016). Thus, parts of both the income and labour of the family members may be allocated outside the agricultural
192sector (Benjamin and Kimhi, 2006; Weltin et al., 2017). Therefore, opportunity costs of agricultural, non-agricultural
193and leisure activities have an important impact on the decision-making.

194Third, decisions are typically not taken by a single person (Burton and Wilson, 2006). This is in part the origin of
195various emotional and cultural attitudes towards farming (e.g. keeping up a family tradition) and especially farm
196succession or exit (Darnhofer et al., 2016; Farmar-Bowers and Lane, 2009; Willock et al., 1999). In addition, for
197family farms, family structures and investment cycles interrelate with farm succession and exit rates. Moreover,
198consumption decisions are also of crucial importance on a household level (Weltin et al., 2017). The family-based,
199and thus atomistic, structure of most of the agricultural sector worldwide implies that collaboration, collective
200actions, and other networks are of crucial importance in decision-making. Empirical evidence shows that networks
201play a critical role in innovation and adaptation of agricultural practices (Moschitz et al., 2015; Schneider et al.,
2022012; Sol et al., 2013). Lastly, the representation of learning, knowledge-sharing and innovation within a family may
203be more complicated than in individual decision-making.

204Fourth, farm(er) agents' decisions are often embedded in multiple temporal cycles. On the one hand, many of the
205agricultural production decisions are rooted in seasonal or annual production cycles. On the other hand,
206agricultural production activities imply the use of capital-intensive assets that are used over longer periods.
207Moreover, several agricultural activities such as perennial crop and livestock production often naturally span
208different periods. Thus, investment decisions, sunk costs, and path dependencies play a crucial role in production
209decisions (Berger and Troost, 2014; Happe et al., 2008). Decisions on the buying or selling of land depend on the
210future prospects of the farm, and on the long-term strategy. Thus, the production decision always has short and
211long-term components. In addition, agricultural production is characterized by a natural lag between production
212decisions and realization of outputs, production cycles, and is soil-dependent, weather-dependent, and technology
213driven (Mehdi et al. 2018). While this may also hold for other economic sectors, the spatial aspect of these
214processes adds complexity via land tenure systems and neighbourhood effects.

215In summary, the decision-making process on farm or farm-household level includes specific components and
216interactions, which could be considered in ABM (see Jones et al., 2016 for a recent review of agricultural and farm
217systems modelling). Thereby, the structure of a conceptual whole-farm model integrates economic, ecological and
218social components (Dent et al., 1995). From a farm systems perspective, the multi-output nature of production and
219associated uncertainties, the importance of non-agricultural activities, the heterogeneous household and family
220characteristics, and the concurrent short and long-term decision-making context are important properties of
221farmers' behavioural patterns.

222 2.3 Farm and agricultural systems perspective in Europe

223The specific characteristics of farmers' decision-making process is important in many contexts worldwide e.g.,
224food security, climate smart agriculture, or natural resource use. To restrict the number of contexts and have a

225 focused and in-depth discussion, we here focus on models applied in a European context. Agricultural systems² in
226 Europe have a set of specific characteristics, and studies of European agriculture address questions that are
227 specific to the European (multifunctional) context including farm structures, agricultural landscapes, and
228 environmental impacts of farming (van Huylbroeck (ed.), 2003). Three specificities emerge from this European
229 perspective:

- 230 • First, with the CAP and other European-level policy schemes such as Natura 2000, as well as national
231 schemes, agriculture in Europe plays out in a very heavily regulated environment, one aspect of which is
232 high levels of subsidisation (Swinnen, 2015). This results in policy priorities, which try to achieve multiple
233 objectives including increasingly prominent environmental targets (Pe'er et al., 2014). Thus, farmers'
234 decisions are very strongly influenced by shifts in policy priorities and decisions on subsidies. This strong
235 regulatory environment also plays out in land zoning. In most places, agricultural expansion is highly
236 restricted in contrast to areas where agricultural expansion is a major process and focus of modelling
237 such as parts of the tropics (Bithell and Brasington, 2009).
- 238 • Second, family farming units that dominate in European agriculture are both production and consumption
239 units. These farms are, however, much more capitalized and embedded in market relations (both for
240 inputs and outputs) and there is much more diversity in terms of access to and use of technology than
241 typical subsistence oriented small family farms in developing countries (Meyfroidt, 2017). In contrast to
242 North America or Australia, average farm size in Europe is much smaller (Eastwood et al., 2010).
- 243 • Third, high opportunity costs of farming (e.g. for land and labour), low farming income as well as high
244 legal constraints trigger two contrasting developments. On the one hand, highly productive land in
245 agglomerations and well-developed areas are increasingly under pressure of intensification. On the other
246 hand, part-time farming and farm exit lead to extensification (de-intensification) and land abandonment in
247 many marginal European areas (Breustedt and Glauben, 2007; MacDonald et al., 2000; Renwick et al.,
248 2013). This causes political tensions between a productivist model of farming and attempts to shift
249 farming into other directions, for example with an increasing relevance of economic diversification on and
250 off the farm, e.g. tourism, on-farm processing and direct sales (Wilson, 2008; Meraner et al. 2015). In
251 contrast to Europe's increasing focus on environmental benefits and diversification, a strictly productivist
252 mindset might be much more prevalent elsewhere in the world.

172 We here define agricultural systems as a subordinate classification of the farm systems representing the com-
18plex interactions and interdependencies between farmers' individual production choices in divers cropping and livestock
19systems, natural systems (including climate, soil, or pests) and social structures such as markets and policies.

253 Thus, for the simulation of phenomena such as food production, agricultural landscapes, land abandonment and
254 environmental impacts in European agriculture, a specific set of research questions emerge about possible
255 reactions to policy changes, farm exit and farmers' replacement and recruitment, and livelihood diversification. In
256 summary, because European agriculture is already quite diverse (Levers et al., 2015), restricting our comparison
257 here to models developed specifically for the context of European agriculture allows us to control partly for the
258 variability in contexts, land uses and farm agents. At the same time, we maintain a relatively large number of
259 models, and thus are able to better understand how differences in the representation of decision-making
260 influences what can be learned from different models.

261 3. Method

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

269 3.1 Literature search

270 To identify the relevant models, we first screened the list of models analysed in the review of agent-based land use
271 models by Groeneveld et al. (2017). We selected all the models that addressed agriculture in a European context
272 (11 models out of 134 publications). In addition, we did the following search in Scopus, Web of Science and
273 Google Scholar to identify the relevant manuscripts: "Agriculture AND agent-based modelling"; "farm AND agent-
274 based modelling". We selected all studies published in scientific journals and excluded all non-European studies
275 (77 out of 193 publications). Finally, we checked whether the remaining articles included agents and some type of
276 decision-making in their analysis. Through this literature search, we found 9 additional models (in 41 publications;
277 for details see Appendix B Table 1) to produce a total of 20 models. In contrast to Kremmydas, et al. (2018), we ex-
278 plicitly included also land-use models that simulate farmers' decision-making and focused on models rather than
279 publications.

280 3.2 Workshop

281 We invited the developers of the most prominent models and further experts on decision-making and agent-based
282 modelling to a Workshop held in January 2017 (see Appendix A for a list of participants). The interaction between

283the experts ensured a critical assessment of review criteria as well as categorization of existing research.
284Moreover, the workshop ensured an extensive reflection on challenges and prospects of representing farmers'
285decision-making in agricultural ABM. For the preparation of the workshop, the developers described their models
286with respect to preliminary review criteria, creating a comprehensive summary comparison of European
287agricultural ABM (see Appendix B, Table 2 summarised and synthesized in Tables 3,4 and 5). During the workshop,
288three tools provided by the Network for Transdisciplinary Research were used to guide the discussions (see
289Appendix C). First, we used the Venn diagram tool (Td-net, 2016b) to elicit the main topics of research and their
290perspective on agent-based modelling approaches. This clarified each participant's expertise and research interest
291in relation to the implementation of farmers' decision-making in agricultural ABM. Second, we applied the Toolbox
292Approach (Eigenbrode et al., 2007; Schnapp et al., 2012) to uncover implicit assumptions and shared
293understandings of the scientific background of ABM in agriculture. On the one hand, this allowed us to identify
294shared views on relevant properties in farmers' decision-making. On the other hand, the tool revealed general
295challenges in ABM development, which built the background for our discussion of the reviewed models. Third, we
296used a Give-and-take matrix (Td-net, 2016) to identify pieces of knowledge or model components that could be
297shared between different workshop participants. This informed the future prospects in developing and applying
298agricultural ABM. The combination of the three methods for co-producing knowledge allowed us to categorize and
299collect existing research and thus build the foundation for our review. Based on the discussion in the workshop
300and the developers' model descriptions, we adjusted and extended initial model descriptions to account for the
301agricultural phenomena addressed (i.e., the purpose of the model). This gave on an overview of the existing use of
302ABM in the context of European agriculture.

303 3.3 Review criteria

304To answer the research questions, we reviewed the existing 20 models in two steps. First, we combined the
305constitutive elements of ABM identified in the different frameworks in Section 2.1 with the characteristic elements
306of the farming system in Section 2.2 and proposed an agriculture-specific framework to describe and compare
307different dimensions in farmers' behaviour in ABM. All 20 reviewed models were described using this framework
308(see 3.3.1). Second, we evaluated the representational sophistication in simulating farmers' decision-making by
309assessing eleven decision-making elements (see 3.3.2). The reviewed models were rated across three levels of
310model functionality, as defined for each criterion in Table 2. Finally, we investigated whether there was a match
311between certain decision-making elements and emerging phenomena in the modelling approaches, allowing us to
312identify patterns between emerging phenomena and the representation of farmers' decision-making.

313 3.3.1 Framework of important dimensions in agricultural ABM

314The review framework we developed brings together the different elements of existing classifications by
315considering three basic elements (Table 1); overview criteria (which can describe any type of model),
316characteristic elements of ABM (which provide the standard criteria for agent-based modelling approaches), and
317the decision-making elements (which describe the specific implementation of the decision-making from a farm
318systems perspective). Details of these three elements are as follows;

3191. *Overview*: We distinguished models with respect to the emerging phenomena they each addressed (e.g. land-
320 use patterns, farm structures etc.), their purpose (e.g. explanatory with full empirical parameterization or
321 explorative with theoretical motivation and partial parameterization) as well as their spatial and temporal
322 extent (Table 3). In general, European agricultural ABM focus on production decisions and the resulting
323 incomes, the development of farm structures, and environmental impacts or landscape changes (i.e., the
324 emerging phenomena represented by the pictograms outside the modelling environment in Fig. 1). In addition,
325 we provide information on the spatial extent of the model (in km²). The importance of these aspects (i.e.,
326 emergent phenomena, purpose and extent) is the trade-off between model complexity (e.g. in terms of
327 parametrization) and interpretability; ABM can quickly become so complex that extensive sensitivity and/or
328 uncertainty analyses are necessary to make their results usable, while simpler models must justify their
329 omissions and the corresponding implications for the simulated outputs.

3302. *Characteristic elements of ABM* (Fig 1.): Since agriculture is a social-ecological system, the comparison should
331 include the description of the fundamental elements of ABM in this context; the biophysical environment, the
332 socio-economic environment, the agents, and the interactions between agents. The biophysical environment
333 includes all the underlying (spatially explicit) data that determines production in the model such as climate, soil
334 or topographical variables. The socio-economic environment includes prices in markets (exogenous or
335 endogenous) and agricultural policies.

3363. *Decision-making elements in a farm systems perspective* (wheels in Fig. 1): We distinguish in this review three
337 dimensions of the decision-making elements: action range, farmers' characteristics and the decision
338 architecture.

339 • *Action range* should reflect the multi-output decision context of the farm including non-agricultural
340 activities, land tenure and/or whether household characteristics are considered. Criteria for the action
341 range of the farm were only rated based on whether they were present in a model or not (Table 4).

342 • *Farmers' characteristics* describe the ability of the models to distinguish the different farmer- or
343 family-specific individual traits such as *goals*, *values*, and *emotions*. These criteria reflect the

344 importance of the various socio-psychological and motivational factors that influence farm decision-
345 making, assuming household members share goals values and emotions.

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

354The chosen dimensions reflect the standard description of the decision-making process in agent-based models
355(see last column in Table 1). However, the characteristics of the farmers' decision context (i.e., multi-output
356decision-making), importance of non-agricultural activities and cultural aspects, as well as the time horizon
357(annual, investment, entry, exit; i.e., the farm system perspective), are of additional importance. The different
358elements (i.e., model environment, action range etc.) described in our framework clearly interact, as indicated by
359the integration of the biophysical and socio-economic environment as a foundation of farmers' decision-making
360(Fig. 1). Thus, it will not be possible to disentangle these elements and dimensions to a specific functionality in
361each model.

362 3.3.2 Assessment of farmers' characteristics and decision architecture in agricultural ABM

363To evaluate the representational sophistication in simulating farmers' decision-making we assessed the eleven
364decision-making elements proposed in the framework for each of the models. Based on the discussion in the
365workshop and the developers' model description, we classified the implementation of the different review criteria
366into three levels of representational sophistication (Table 2). After the workshop, the developer of each model
367reviewed the resulting assessment (Table 5). It is important to note that the rating with respect to different
368aspects of the decision-making process by no means refers to an assessment of the quality of the models, which
369is clearly dependent on purpose and research questions in the corresponding study and would go beyond the
370purpose of this review.

371 4. Results

372 4.1 Characteristic elements of reviewed ABM

373All the models reviewed used farms as their decision-making unit. Four out of the 20 reviewed models included
374non-farming agents such as institutional or governmental agents (CRAFTY, FEARLUS), nature organizations and
375estate owners (RULEX) or municipalities and national parks (SERD). A majority of the models addressed spatially
376explicit land-use changes and the corresponding landscape pattern as an emerging phenomenon (16 out of 20
377models). All these models had a spatially explicit representation of the biophysical environment, which varies from
378synthetic landscapes to high biophysical realism. Fully parameterized models covered, on average, a smaller
379spatial extent, even though ABMSIM, AGRIPOLIS and MPMAS also cover larger landscapes (i.e., > 500 km²). Two
380models (FOM, GLUM) focused only on crop choices without focusing on the aggregation at the landscape level.
381These two models had a specific, complex representation of the decision-making. SWISSLAND did not reflect
382spatially explicit land-use patterns due to the non-spatial nature of the underlying data from the Farm Accountancy
383Data Network (FADN), and in one case, modellers addressed manure allocation (Van der Straeten) for which the
384spatial representation focused on distances rather than land-use patterns. The review also showed that less than
385half of the models (8/20) considered off-farm income or labour allocation in their simulations. The consideration
386of non-agricultural activities was via exogenous drivers (e.g. opportunity costs or wages) or derived from FADN. In
387contrast, only three models also included household consumption in farmers' decision-making. In AGRIPOLIS and
388MPMAS, consumption and savings were again linked to farmers' investment decision.

389The interaction between farmers in most of the models was based on land markets or another form of land
390exchange. ABSIM and SERA specifically focused on different types of auction mechanisms in land markets. Not all
391models using land markets also differentiated between rented and owned land. However, only FEARLUS-SPOMM,
392in the context of the adoption of biodiversity measures, and SAGA, in the context of the adoption of irrigation
393technologies, fully addressed social interactions between farmers. In FEARLUS, agents had the ability to check the
394yields from their neighbours and, based on an aspiration threshold, to either leave land-use unchanged or imitate
395the land-use choice of its neighbours. In addition, it also considered interactions between farmers and government
396actors. In the SAGA and the FOM model, social interactions were implemented via the so-called CONSUMAT
397approach (Jager and Janssen 2012). This approach determined four behavioural strategies, i.e., repetition,
398optimization, imitation and inquiring based on satisfaction of and uncertainty faced by the farmer. In these
399models, agents who were uncertain with respect to the benefits of a given farm activity or technology will imitate
400other agents' activities. Moreover, in SAGA, imitation was mediated through a social network in which a strong link
401joins peers who had similar farm characteristics and were located nearby. By contrast, in MPMAS, a threshold
402approach was applied that allowed simulation of different types of adopters such as innovators, early adopters
403and laggards. The Vista model allowed only for a certain type of farmers (so-called absentees) to imitate their

404neighbours. Finally, CRAFTY also represented social networks that allowed modification of productivity and
405competitiveness between agents.

406 4.2 *Decision-making elements in a farm systems perspective*

407A key advantage of ABM is to consider different goals and values in the farmers' decision-making (13/20). To
408represent goals, many models used farmer types derived from surveys and/or census data such as hobby-, part-
409time-, conventional or business oriented farmers. The different agents then varied in their decision-rule (Valbuena,
410APORIA, CLUM and SPASIM) and/or their parametrization (ALUAM, CLUM, CRAFTY). Two models used decision
411trees as algorithm for farmers' decision-making representing a lexicographic order of goals (Vista, SERD). These
412types of models set different decision rules for agents depending on the farmers' and farm characteristics. RPM
413assumed different "farming styles" as a result of the differences among the farmers in their labour and capital
414costs and their willingness to support agriculture from other income sources. In RULEX, farmers were
415differentiated through behaviour types i.e., expanding, shrinking, intensifying or innovating. The model allocated
416agents to behaviour based on a logistic probability function using farmers' attributes (i.e., age, size etc.) as
417explanatory variables. In FEARLUS, SAGA, FOM and CRAFTY, heterogeneity in goals could also be determined by
418varying threshold such as aspiration, tolerance or competition levels.

419Beliefs or values were in most case studies considered as part of the farmers' typology. For example, SPASIM
420used the attitude of the heir to simulate whether a traditional farm had a successor. APORIA, CRAFTY and CLUM
421used a utility function in which different goals could be weighted to reflect underlying beliefs and values. In the
422reviewed applications, however, this model functionality was only mentioned as a possibility but not actually used.
423Thus, there is currently no model that includes endogenous simulation of underlying beliefs to determine
424preferences or goals in European ABM. Furthermore, emotions are not reflected in any of the reviewed models
425despite the importance of affective factors described e.g. in Balke and Gilbert (2014).

426Risk management and decision-making uncertainty was considered in only a few models (6/20). GLUM used profit
427maximization and the minimization of risk (i.e., the standard deviation of total income related to expected gross
428margin) as elements of the farmers' goal function. In MPMAS, penalties for more risky crops could be considered
429in the objective function. In those models using the CONSUMAT approach, uncertainty was a key variable to
430determine farmers' behaviour. In SAGA the uncertainty level was defined as the ratio between a farmers' current
431income and his predicted income, which was derived from their past income using an exponential smoothing
432algorithm. Similarly, FOM related the farmer's certainty to the average performance within the previous five years
433(i.e., the farmer was uncertain if their results have been consistently below a minimal satisfaction level). In
434addition, agents in CRAFTY could have individual variation in give-up and give-in threshold parameters to reflect

435uncertainties in their decision-making. In SRC, the discount rate used is also determined by the personal risk
436aversion of the agents. Thus, the consideration of risk management and decision-making uncertainty is currently
437very limited in European ABM despite its importance in agricultural production decisions.

438In many European ABM, farmers were assumed to have perfect knowledge of the value of the variables and they
439did not have a specific representation of how they obtained information. For example, the proportion of landscape
440in commercial vs. traditional farming types can influence decisions to change agent type or to exit farming in
441SPASIM, but it is unclear how individual farmers would come to know this information about the landscape-level
442state. Specific interactions between the biophysical environment and the agents' behaviour were modelled for the
443interaction between bird population and farmers land use decisions in APORIA, changes in drought conditions in
444SAGA, and the level of biodiversity in FEARLUS (mediated through a government agent). This allowed adjusting the
445farmers' management practice according to the environmental outcome of their past decisions.

446In addition, a few models used some form of memory about past decisions, prices or outcomes as a factor in the
447farmers' decision-making. In Vista, FOM and SAGA, memory of past income was projected into the future and
448leads to adaption of land-use decisions. In AgriPoliS, agents revised their expectations with respect to output
449prices periodically by calculating expected prices for land. In SERD, a weighted moving average of the prices in
450past periods was used to update price information for the farmers. In Valbuena, agent actions like 'cut', 'keep' or
451'plant' landscape elements depended on previous choices. Similarly, agents in GLUM accumulated knowledge on
452crops, which increased the possibility that the same crop was chosen (reflecting path dependencies). In APORIA,
453farmers had a "knowledge base" that contained all the information about land uses and other factors that
454informed an agent's decision. These approaches allowed the agents to "learn" from past behaviour or outcomes.
455However, the consideration of feedbacks between farmer networks, collectives or organizations was seldom
456addressed. Learning through adaptation of behaviour of others was only implemented in SAGA through imitating
457the adoption and in FEARLUS, in which agents learn by storing new cases i.e., particular land uses.

458Thus, the review suggested that models with high sophistication in the representation of perception, interpretation
459and evaluation (APORIA, SAGA, FEARLUS), goals (APORIA, GLUM), learning (FEARLUS), decision-making rules
460(VISTA, SAGA, FOM) and social interactions (SAGA, FEARLUS) are generally of the explorative or explanatory type,
461without a full parameterization of every aspect of the decision-making process. In addition, values and learning, as
462well as affective aspects of farmers' decision-making, were hardly considered. Moreover, aspects of risk and
463uncertainty were not often represented in existing models. While many models included some stochastic
464component to reflect the variability of yields or utilities, this information was not considered within the decision-
465making rules.

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

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

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

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

488 In summary, the review showed that, depending on the focus of the corresponding ABM, the decision-making
489 process implemented was more or less tailored to characteristics important in a farm systems perspective. The
490 multi-input and multi-output aspects of farming systems were specifically well represented in models addressing
491 emissions from agriculture for which a detailed representation of the production technology is warranted. Models
492 with a specific focus on farm structural change and inter-temporal decisions addressed the temporal context of
493 farmers' decision-making in more detail. Off-farm opportunities and labour allocation were considered in many
494 models but without a specific logic in which context or with respect to a specific phenomenon addressed.

495Cognitive, affective and social aspects were included in many European agent-based models but with different
496degrees of representational sophistication and addressing no shared problem domain.

497 5. Discussion

498Agent-based modelling approaches in the European agricultural sector potentially have many advantages. In
499particular, the “bottom up” approach, through considering heterogeneity in decision-making and representing
500spatial and social interactions, complements other scientific policy evaluation tools such as integrated
501assessment tools (van Ittersum et al., 2008), (partial) equilibrium models (Schroeder et al., 2015), economic
502experiments (Colen et al., 2016) or econometric approaches (Imbens and Wooldridge, 2009).

503However, are existing ABM equipped with the properties and behavioural functions capable of generating reliable
504and robust simulations? It is clear that the properties to be considered in a model depend on the purpose of the
505study. Increasing complexity in representations of farmers’ decision-making may not necessarily be useful or even
506meaningful (Sun et al., 2016). Thus, this review does not explicitly judge the quality of each model but tries to
507describe the current state of research as a whole, and to scrutinize whether particular agent decision-making
508formulations are more appropriate for some particular decision-making situations rather than others (Parker et al.,
5092003).

510 5.1 *Specific properties of farm systems important in modelling farmers’ behaviour in ABM*

511Based on a farm systems perspective (see e.g. Jones et al., 2016), we argue that the multi-output nature of
512production, the coexistence of agricultural and non-agricultural activities, the heterogeneity of household and
513family characteristics and the concurrence of short and long-term decisions are important properties of farmers’
514decision-making. Our proposed framework to describe agricultural ABM is rooted in the categories of existing
515frameworks (Parker et al., 2008), classifications (Schlüter et al., 2017; Balke and Gilbert 2014) and the ODD+D
516standard protocols to describe decision-making in ABM (Müller et al., 2013). The benefit of our framework is that it
517concretises and complements existing elements of describing agricultural ABM from a farm systems perspective.
518Thus, the framework could be extended for use in describing farmers’ decision-making in several contexts and
519shed light on the agent-based modelling of agricultural systems in other parts of the world. We add to recent
520reviews of decision-making in ABM (e.g. An, 2012; Groeneveld et al., 2017, Kremmydas et al., 2018), by focussing
521on models that address agricultural policy aspects in the context of European “multifunctional” agriculture and
522show that the dimensions and elements presented help to categorize and compare decision-making processes in
523ABM.

524 5.2 *Types of decision-making mechanisms in European ABM*

525Existing empirical research suggests that farmers' decision-making is strongly influenced by individual values,
526attitudes and preferences (e.g. Benjamin and Kimhi, 2006; Burton and Wilson 2006; Weltin et al., 2017) and
527farmers' interactions through networks (Moschitz et al., 2015; Schneider et al., 2012; Sol et al., 2013). This implies
528that reliable and robust models of agricultural systems could profit from more modelling effort in differentiating
529farmers' decision-making according to their individual and social characteristics. Therefore, there seems to be
530considerable potential for European ABM to increase the sophistication in representing farmers' decision-making
531mechanisms and interactions with each other.

532Our review implies that current ABM applied to European agriculture address farmers' decision-making processes
533on various levels of sophistication depending on the purpose of the model and the corresponding research
534questions. We find models to be sophisticated in the representation of farm exit and entry decisions, as well as the
535representation of long-term decisions and the consideration of farming styles or types using farm typologies.
536Perceptions, Interpretation and evaluation also occur in many models. There are considerably fewer attempts to
537model farmers' emotions, values, learning, risk and social interactions in the different case studies. In addition,
538non-agricultural activities and household-level decisions are also rarely considered in European agricultural ABM,
539despite their relevance (Meraner et al., 2015; Weltin et al., 2017).

540The scarcity of attempts to model aspects such as values or social interactions is somewhat in contrast to ABM in
541other regions and farming systems. For example, in the context of social interactions and neighbourhood effects
542and their influence on farmers' behaviour there exist various empirical and theoretical agent-based models (e.g.,
543Bell et al., 2016; Caillault et al., 2013; Chen et al., 2012; Manson et al., 2016; Rasch et al., 2016; Sun and Müller,
5442013). Also, with respect to decision-making rules, there seems to be greater variety outside the European context
545(e.g., Acevedo et al., 2008; Janssen and Baggio, 2016; Le et al., 2008; Le et al., 2012; Manson and Evans, 2007;
546Matthews, 2006; Rebaudo and Dangles, 2011; Schreinemachers and Berger, 2011, Berger et al., 2017). In a
547developing country context, the MPMAS model has recently been applied to the assessment of collective action of
548coffee farmers in Uganda (Latynskiy and Berger, 2017). Looking beyond the agricultural sector, the scope for
549increasing complexity in the representation of farmers' decision-making is even broader, as the reviews by Balke
550and Gilbert (2014) and Utomo et al. (2017) show.

551 5.3 *Representation of farm behavioural in specific problem domains*

552ABM in the European context focus on land-use and land-use changes on various spatial and temporal levels.
553Land markets represent the key mechanism representing farmers' interactions in almost all of the reviewed
554models. We did not, however, find any pattern with respect to the spatial extent used in the application of the

555models. Explanatory models with empirical parameterization usually have a shorter temporal extent compared to
556more abstract or theoretical motivated models.

557Models focusing on farm structural change have a particularly complex representation of the temporal aspects, as
558well as farm entry and exit decisions. The simulation of environmental aspects such as nitrogen or greenhouse
559gas emissions provide a detailed representation of the farmers' production technology and thus are usually more
560sophisticated with respect to the multi-output nature of production.

561Models that address the implementation of agri-environmental measures or the assessment of landscape
562changes in the agricultural sector do not seem to focus on specific domains or properties of farmers' decision-
563making process. Off-farm opportunities and labour allocation are considered in many models but without
564addressing a specific phenomenon. Complex representations of decision-making with respect to cognitive or
565social aspects are currently not, or only partly, implemented in explanatory models with full empirical
566parameterization.

567This suggests that there are trade-offs between a complex representation of farmers' decision-making and the
568detailed representation of multi-output production systems, non-farm opportunities and complex long-term
569decisions of European farms with full parameterization. Thus, there is considerable potential for the reuse of
570parameters, modules or code within this research community, as postulated by several scholars (Bell et al., 2015;
571Schulze et al., 2017). This can be especially fruitful for agricultural ABM since they often focus on specific aspects
572of decision-making but are applied to the same emerging phenomenon (e.g. in the context of agri-environmental
573measures). This practice would not only save modelling and validation efforts, but also increase the replicability of
574the studies using the model. Meanwhile, it indicates opportunities to improve the representation of farmers'
575decision-making in European ABM.

576 5.4 Challenges and prospects of agricultural ABM

577Challenges and prospects for agricultural ABM were also critically discussed in the workshop. There was a
578consensus that increasing diversity in decision-making and the integration of social interactions in agricultural
579ABM is of crucial importance to model emerging phenomena in agricultural systems. The increase in
580representational sophistication could even be used to address additional aspects such as the consideration of
581entrepreneurship, strategic decision-making or interactions along the value chain.

582To increase the realism of the representation of agricultural system and the use of ABM in policy assessment,
583there seems to be an opportunity to align the above mentioned two streams of literature: Those models that
584include multi-output production systems, non-farm opportunities and complex long-term decisions and those

585models addressing more complex representations of decision-making considering also values, risk, learning and
586social interactions. To this end, the production of more generalizable results in the various models could inform
587one another and collectively build up a picture of major behavioural processes in farm systems. This would offer
588the opportunity to make an informed decision on where to account for specific dimensions or elements of the
589decision-making process to improve representation of the way people act. This could support the future
590development of better models to support agricultural policy making by investigating what is important and what
591works for which question or farming system. To lay the ground for such multi-model inter-comparison, a first step
592could be to use models that address the same emerging phenomena in the same case study to allow for a specific
593evaluation of the different model characteristics. This would allow direct identification of the relevant properties
594and behavioural patterns of the farmer representation that might increase the reliability and robustness of
595simulations.

596There are, however, some well-known challenges with the aspiration to represent real systems in an adequate
597manner and at the same time increase the sophistication of the decision-making process. These challenges apply
598to ABM also beyond the European context. First, the difficulties of parameter calibration and proof of validity
599increases with model complicatedness, i.e. the challenge of parsimonious system presentation. Empirical ABM
600have been criticized for their large data requirements and high uncertainty of input parameters (Magliocca et al.,
6012015; O'Sullivan et al., 2015; Troost and Berger, 2015). While ignoring highly uncertain processes may give illusory
602certainty in other modelling approaches, the communication and applicability of ABM in ex-post and ex-ante
603evaluations of agricultural policies are still crucial challenges.

604Second, there is a danger of creating 'integronsters' that are difficult to understand and become a black box for
605stakeholders and users (Bell et al., 2015; Voinov and Shugart, 2013). Third, the communication of the model may
606become more challenging, especially if models will be used in policy evaluations that also need a comprehensive
607description of the model for non-scientists (Müller et al., 2014). Fourth, "mid-level" models between simple (often
608theoretical) and complex models may create new risks such as over-specification or unnecessary complexity (Sun
609et al., 2016). Thus, the increase of sophistication in representing decision-making processes may intensify these
610challenges of calibrating, validating and communicating agricultural ABM.

611Existing literature suggests that there are various approaches to tackle these challenges, with a broad stream of
612literature on do's and don'ts in designing ABM which should be considered in the development, as well as in
613sharing and comparing of these models (Abdou, et al., 2012; Bell et al., 2015; Helbing, 2012; Macal and North,
6142010; Smajgl and Barreteau, 2014). Using careful software engineering techniques is an essential pillar in this
615context. More importantly, aligning a proper representation of agricultural systems with complex decision-making

616in ABM must include careful sensitivity analysis and model verification including a thorough and transparent unit-
617testing (Le et al., 2012; Lee et al., 2015; Ligmann-Zielinska, 2013; O'Sullivan et al., 2015; Troost and Berger, 2015).
618Machine learning and the development of surrogate meta-models can help to efficiently explore parameter space
619and effectively improve calibration exercises (Lee et al., 2015, Pereda et al., 2017). In addition, pattern-oriented
620modelling is an approach to avoid making an ABM become over-parameterized and lose predictive power (Grimm
621et al. 2005, Grimm and Railsback, 2012). Moreover models should be as transparent as possible (e.g. by using
622ontologies in the computer science sense of a formal representation of conceptualisation, Livet et al., 2008; Polhill
623and Gotts, 2009), or by using standard protocol ODD+D (Müller et al., 2013, Kremmydas et al., 2018) or model
624design patterns (Parker et al., 2008). Various authors also suggest increasing the reuse and sharing of model
625modules, codes or sub-models, through open-source development for example OpenABM.org (Bell et al., 2015;
626Schulze et al., 2017). Hybrid models that tightly integrate or combine two or more approaches could be a
627promising direction in this context (O'Sullivan et al., 2015). The give-and-take exercise at the workshop showed
628that the model developers and experts in farmers' decision-making are keen to share knowledge, data and model
629codes (Appendix C, Fig. 3).

630Furthermore, some authors suggest that modellers should search for and engage with other (social) scientists
631studying decision-making (Meyfroidt, 2013; Schulze et al., 2017). This could improve plausibility of models with
632regard to farmers' behaviour from a psychological point of view (Schaat et al., 2017). The Venn diagram exercise
633during the workshop (Appendix C, Fig. 1) implied that the goal of most of the agricultural agent-based modellers in
634Europe is to better reconcile empirical data and theoretical foundations including other modelling approaches, or
635at least to attentively monitor developments in the other fields. Also here, the Give-and-Take matrix showed that
636there would be actually many practical opportunities for collaboration between experts on decision-making and
637agent-based modellers. Agent-based modellers should thus proactively consider opportunities to work together on
638model comparison and integration in research collaborations.

639The discussions at the workshop resulting from the toolbox approach confirmed prospects and bottlenecks in the
640process towards better reuse, model inter-comparison, hybrid modelling and model ensembles. Data availability,
641reliability and the fact that models are usually built for different cases are seen as critical challenges (see
642Appendix C, Fig. 2). Particularly, data collection with respect to interactions (e.g. among farmers) is challenging.
643Here, new data sets such as those collected with the help of mobile phone apps could be of added value (Bell,
6442017). Finally, the validation of the models, or at least of parts of the models, and their trustworthiness remains a
645major challenge for robust and reliable modelling (O'Sullivan et al., 2016; Polhill et al., 2016). Experts at the
646workshop, however, were also convinced that ABM is a powerful tool to explore and understand potential decision-

647making, and so complement social science and other disciplines, rather than simply adopting findings in
648calibration. In addition, the view was that ABM form an ideal vehicle to integrate social sciences also with natural
649sciences, something that is urgently needed if we want to address today's most pressing environmental problems.

650 **6. Conclusion**

651For reliable and robust ABM that allow for the assessment or evaluation of policy instruments, a realistic
652representation of the farmer's decision context is crucial. This is of specific importance in the European context
653where the CAP substantially shape the landscape of farm systems via affecting farmers' decision-making. We
654reviewed 20 European agricultural ABM with a focus on the representation of the decision-making process. The
655results showed that, depending on the focus of the corresponding ABM, the decision-making process includes
656different elements that we consider to be important from a farm systems perspective. The lack of consideration of
657many values, social interactions, norm consideration, and learning in farmers' decision-making across European
658agent-based models leaves considerable room to improve the representation of farmers' decision-making and a
659better representation of an agricultural systems perspective in ABM. This presents an opportunity to align the
660simulation of farmer's decisions more closely to actual decisions. Our hope is that this view supports the dialogue
661not only between developers of agricultural ABM but also the broader community of agricultural systems
662modellers and data-driven social sciences. This could fertilize more coordinated and purposeful combinations of
663ABM and other modelling and empirical approaches in the agricultural sector beyond the European perspective.
664This is ultimately the key to developing reliable explanatory models of agricultural systems and their use in ex-ante
665or ex-post agricultural policy evaluations.

666

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670versions of the manuscript.

671.

672Table 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?
ABMCharacteristic elements of	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 Policies	Economic structures Institutional/Political constraints	Social environment		What are the exogenous factors/drivers of the model?
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				
	Farmers' characteristics	Household (characteristics & consumption)				
		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 biophysical 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	Selection	Cognitive	How do agents make their decisions? Are the agents	

			strategy			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?

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676Table 2 Review criteria to compare representation of decision-making elements in a farm systems perspective

Review criteria	Explanation	Levels of representing sophistication in farmers' characteristics and decision-architecture		
		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

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678 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 and Wieck (2014)	Spatially explicit land-use, farm structures	A	1300 km ² 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 km ² 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 km ² 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 km ² 50 years	Land manager	Land market	Spatially explicit (biophysical properties)	Exogenous	Activity based subsidies or restrictions
CRAFTY Brown et al. (2016)	Land-use change at European scale	B	1600 km ² 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 policies (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 km ² temporal unrestricted	Farmer types (profit maximizer, yield maximizer, environmentally-oriented farmer)	Neighbour imitation	Spatially explicit	Exogenous	-
GLUM Holtz and Nebel (2014)	Transition from rainfed to irrigated agriculture	B	16'000km ² retrospective (1960-2010)	Farm types (part-time, family farm, business oriented)	Observing other agents' activities	-	Exogenous (no prediction)	Relevant CAP policies
MPMAS (Germany) Troost et al. (2015)	Regional agricultural supply, land-use, farm structures, participation in agri-environmental schemes	A	1300 km ² 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 km ² 30 years	Individual farms	Land market	Spatially explicit (vegetation, topography)	Exogenous	Relevant payment schemes
RULEX Bakker et al.	Land markets, spatially explicit land use change,	A	300 km ² retrospective	Land owners: individual farmers (subdivided in	Agents buy and sell land from/to each	Climate change affects hydrological	Exogenous	Policies for implementing national ecological network

(2015)	rural depopulation, farm size growth, intensification.		ve (2001-2009)	categories), individual estate owners, and nature conservation organizations	other.	soil properties		
SAGA van Duinen et al. (2016)	Adoption rates of irrigation technology, water demand, agricultural production	B	138 km ² 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. (2014)	Land use patterns	B	606 km ² 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 km ² 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 km ² 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 km ² 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	600km ² 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 km ² 50 years	Individual farmers, in typology groups (innovative, active, absentee, and retiree)	Land market, neighbour imitation	Spatially explicit (agricultural suitability)	Exogenous	CAP payments

679*Purpose of modelling: A Explanatory with full empirical parameterization; B Explanatory with empirical context, but abstracted parameterization; C Explorative with theoretical motivation and partial
680parameterization

681

682Table 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	-

683

684 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

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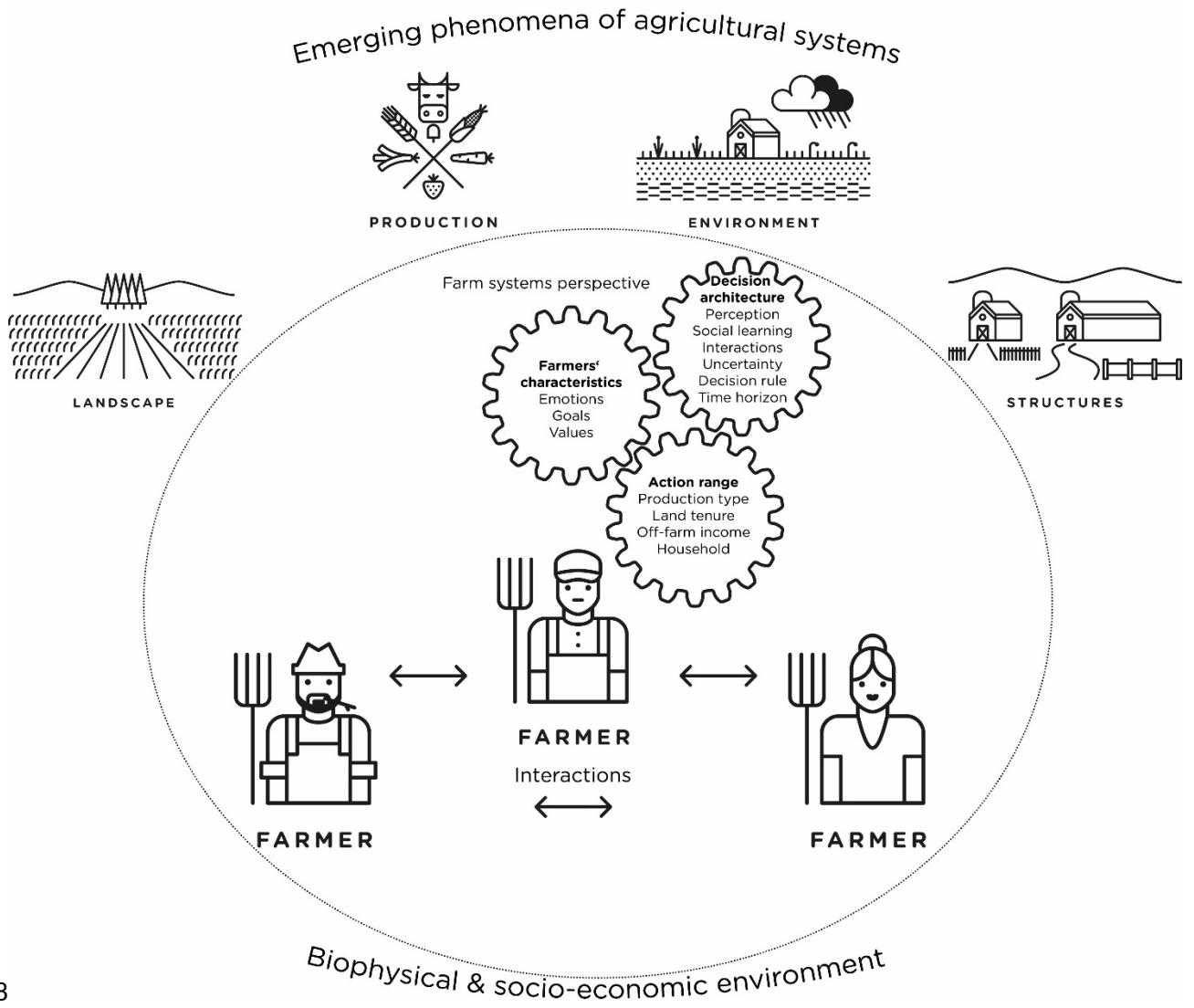
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Valbuena	A	1	1	1	1	1	1	2	2	2
VISTA	A	1	1	1	2	1	2	2	2	3
APORIA	B	1	2	1	1	1	2	3	3	1
CRAFTY	B	1	2	2	2	1	1	2	2	1
GLUM	B	1	2	3	1	2	2	2	3	1
SAGA	B	2	1	3	3	1	3	3	2	1
SERA	B	1	1	1	1	1	1	2	1	1
SERD	B	1	1	1	1	1	2	2	2	2
SRC	B	1	1	2	1	2	1	1	1	1
Van der Straeten	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

685

686Figure 1. Dimensions of farmers' decision-making and simulated emerging phenomena in European
687agricultural ABM

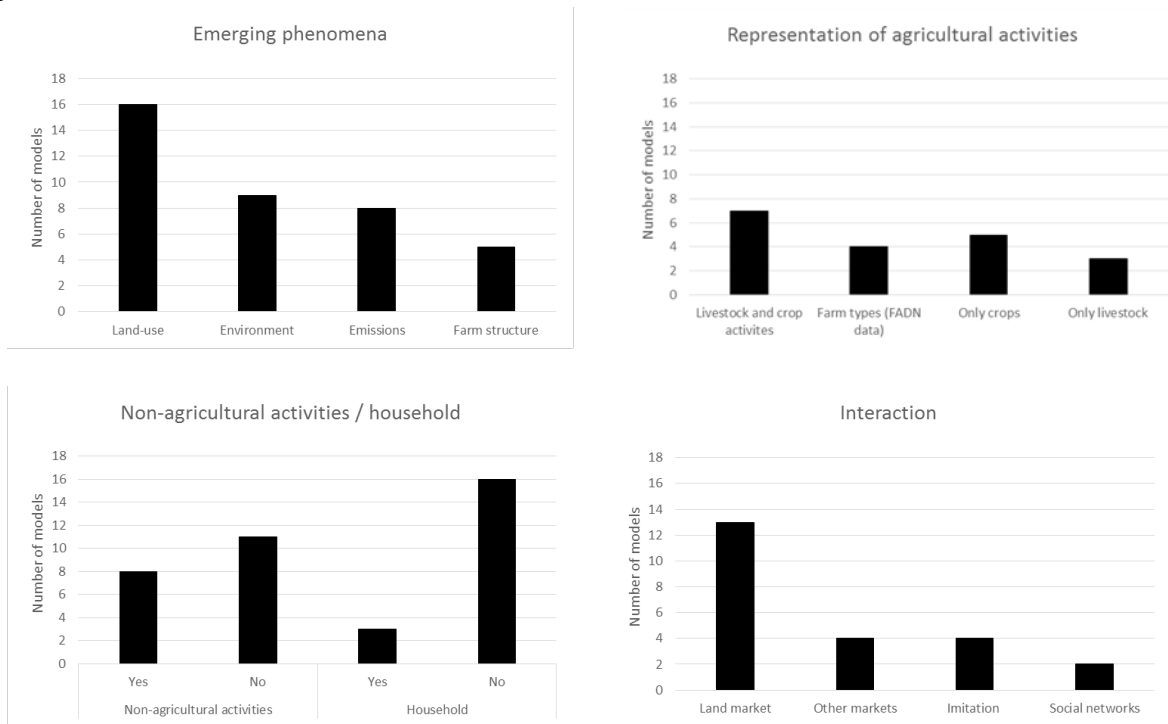


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691Figure 2. Emerging phenomena, agricultural activities, non-agricultural activities and interactions in European
 692ABM
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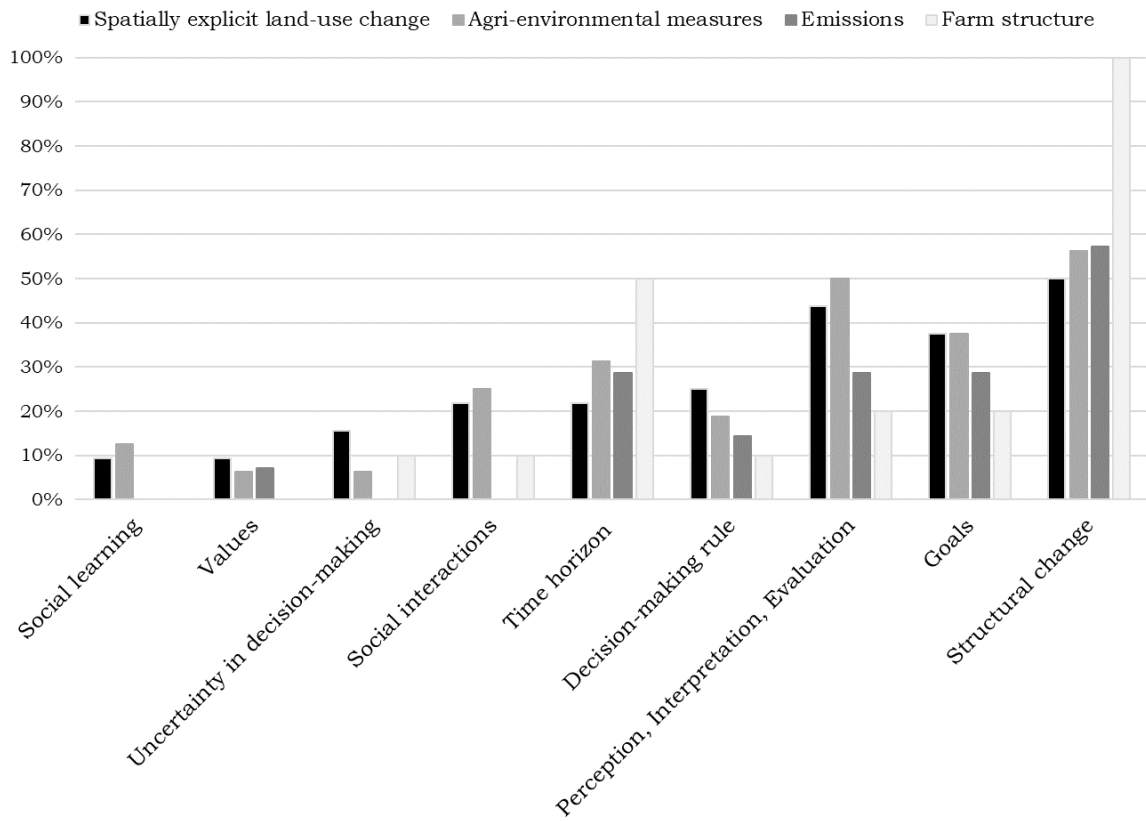


694Note: For emerging phenomena and interactions, models can be counted more than once.

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697Figure 3. Representation of complexity in decision-making elements with respect to emerging phenomena
698simulated in reviewed ABM



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701Note: A value of 100% indicates that all models addressing the phenomena have a level of representational sophistication
702of 3 (in Table 5) for the corresponding review criteria. For example, all models that address farm structures have also a
703sophisticated representation of family farm cycles, entry and exit decision, or succession probability. A value of 0% implies
704that if a specific emerging phenomenon is addressed, the corresponding review criteria has a level of representational
705sophistication of 1 (in Table 5). For example, none of the models that address farm structures represents social learning.

706

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