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Gotts, NM, van Voorn, GAK, Polhill, JG, de Jong, E, Edmonds, B , Hofstede, GJ and Meyer, R (2019) Agent-based Modelling of Socio-Ecological Systems: Models, Projects and Ontologies. *Ecological Complexity*, 40 (Part B). p. 100728. ISSN 1476-945X

DOI: <https://doi.org/10.1016/j.ecocom.2018.07.007>

Publisher: Elsevier

Version: Accepted Version

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Agent-Based Modelling of Socio-Ecological Systems: Models, Projects and Ontologies

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Abstract

Socio-Ecological Systems (SESs) are the systems in which our everyday lives are embedded, so understanding them is important. The complex properties of such systems make modelling an indispensable tool for their description and analysis. Human actors play a pivotal role in SESs, but their interactions with each other and their environment are often underrepresented in SES modelling. We argue that more attention should be given to social aspects in models of SESs, but this entails additional kinds of complexity. Modelling choices need to be as transparent as possible, and to be based on analysis of the purposes and limitations of modelling. We recommend thinking in terms of modelling projects rather than single models. Such a project may involve multiple models adopting different modelling methods. We argue that agent-based models (ABMs) are an essential tool in an SES modelling project, but their expressivity, which is their major advantage, also produces problems with model transparency and validation. We propose the use of formal ontologies to make the structure and meaning of models as explicit as possible, facilitating model design, implementation, assessment, comparison and extension.

Keywords— Socio-ecological system; Agent-based model; Complexity; Ontology

1. Introduction

Socio-Ecological Systems (SESs) consist of interacting biogeophysical components and social actors (individual and collective). They are invariably complex in their dynamics. Most if not all of the systems providing essential ecosystem services to humanity can be classified as SESs; examples include fisheries, agricultural and food systems, and managed forestry systems. The study and governance of SESs have attracted considerable attention, because many are under increasing pressure from anthropogenic sources: growing population, over-utilization, pollution, and climate change (Steffen et al., 2011; Rist et al., 2014). Many concepts currently in use in relation to SESs, including that of resilience, and related notions such as tipping points,

28 arise from study of the complex dynamics of these systems. Computational models can help to
29 unravel how these system properties emerge. Modelling guidelines are available for instance in
30 the fields of water management (STOWA/RIZA, 1999; Jakeman et al., 2006; Liu et al., 2008) and
31 environmental policy modelling (Janssen et al., 2005; van der Sluijs et al., 2005; Schmolke et al.,
32 2010; van Voorn et al., 2016), often based on the generic cycle of model development and analysis
33 described by Refsgaard and Henriksen (2004). However, the human side of SES modelling has
34 been given relatively little attention in comparison to the ecological side, and models where social
35 and ecological components are fully integrated are rare. This paper focuses on how to remedy
36 that situation.

37 Environmental models used for policy assessments generally include social actors and insti-
38 tutions only implicitly, e.g., as parameters to increase or decrease certain system drivers, or as
39 output indicators regarding the fulfillment of certain requirements. For example, many assess-
40 ments of ecosystem services assume economic rationality, which implies that pricing mechanisms
41 and technological innovations can adequately ensure system resilience. Such assessments of-
42 ten include social drivers and impacts among those they consider, but without modelling the
43 decision-making or social interactions of relevant groups of actors, see for example Vidal-Abarca
44 et al. (2014). This is regrettable from both a scientific and a governance point of view con-
45 sidering that policy usually targets social actors. For example, a farmer may directly affect
46 biogeophysical system components through the use of fertilizer or pesticides, but policy targets
47 the farmer, and not all farmers behave in the same way (see Feola and Binder (2010), and ref-
48 erences therein). More generally, not only do different societies organize themselves in different
49 ways (Hofstede et al., 2010), but psychological processes and attributes vary systematically across
50 cultures (Smith et al., 2006). These differences are of the utmost importance to the functioning
51 of SESs. The resilience and sustainability of social and organizational systems, is as important as
52 those of natural systems (Cutter et al., 2010). For instance, social norms have developed among
53 fishers in the Philippines tuna fishery that prevent the simultaneous use of all available fishing
54 sites, creating ‘safe patches’ for tuna that may thus improve resilience against over-fishing (Libre
55 et al., 2015). If these norms were to collapse, perhaps due to external pressures for “economic
56 rationality”, the fishery itself could follow.

57 Even where the need to use social science approaches is conceded, their role is frequently
58 unduly limited. For example, Daily et al. (2009) say of the assessment of ecosystem services:
59 “[t]he biophysical sciences are central to elucidating the link between actions and ecosystems, and
60 that between ecosystems and services (biophysical models of ‘ecological production functions’).
61 The social sciences are central to measuring the value of services to people (‘economic and
62 cultural models’).” But this does not do justice to the role of social processes in SES. They
63 are more resistant to modelling than biogeophysics, as we discuss. Nevertheless, as indicated by
64 the examples above, and more broadly work such as that of Ostrom (2009), we consider explicit
65 inclusion of social components in SES models essential.

66 The inclusion of social behaviour raises legitimate concerns in modelling circles about the
67 consequent demands for data, and the objection that with many tuneable parameters, they can
68 produce any desired output. This forces us to think more explicitly about how we model, why
69 we model and the context of modelling in order to choose the most appropriate approach. In
70 this paper, we consider key issues in modelling SESs that arise when including social actors in
71 models, and suggest ways to deal with them. We conclude that agent-based models (ABMs), in
72 which the decision-making of human actors is explicitly represented, are key to SES modelling
73 that does justice to the social aspect of such systems. We concede, however, that agent-based
74 modelling currently suffers significant limitations and drawbacks, particularly with regard to
75 validating, comparing and combining models (Schulze et al., 2017). We therefore propose an
76 approach to ameliorating these disadvantages, based on a shift of focus from *models* to *modelling*

77 *projects*, and on the use of formal ontologies (Gruber, 1993).

78 The paper is structured as follows. In Section 2 we review the properties of SESs, and
79 approaches to assessing them. In Section 3 we look at the roles of data and theory, the significance
80 of modelling aims, and a range of modelling approaches. Section 4 outlines methodological
81 issues concerning agent-based modelling, focusing on the role of ontologies. A summary of our
82 conclusions, and some directions for future work, follow in Section 5.

83 2. Why SES modelling is needed, but difficult

84 2.1. The complexity of SES

85 SESs are characterized by considerable human influence (it is doubtful if there are now any
86 ecosystems on the planet where such influence can be discounted). SESs display additional *kinds*
87 (not just degrees) of complexity resulting from social interactions among human individuals or
88 collectives. We first specify what we mean by the complexity of a system.

89 Systemic complexity has no generally agreed definition, but one useful approach is that of
90 Auyang (1999), according to whom a complex system can be defined as one that “cannot be
91 successfully approximated as a collection of (similar) constituents each responding independently
92 to the situation jointly created by all”. A clear counterexample is a molecular gas in equilibrium:
93 each molecule can be regarded as responding to the temperature and pressure of the whole,
94 which in turn are simple outcomes of the spatial and velocity distributions of the collection of
95 molecules. Another example – at least in theory – is a “perfect market”: each agent is assumed to
96 act independently, and to respond to price signals which it cannot significantly affect by its own
97 behaviour. Adopting such a definition of systemic complexity puts the emphasis on the system’s
98 mereology – the relationships of its parts to each other and to the whole (Gruszczyński and Varzi,
99 2015), rather than on computational properties of algorithms needed to simulate it or reproduce
100 data streams from it, or other properties of observed quantitative variables. When a reduction
101 to independently responding components is not possible, understanding the system requires the
102 identification of intermediate levels of structure. Focusing on the system’s mereological features
103 allows us to identify subclasses of systemic complexity, which illuminate the modelling challenges
104 associated with each kind (see Fig. 1).

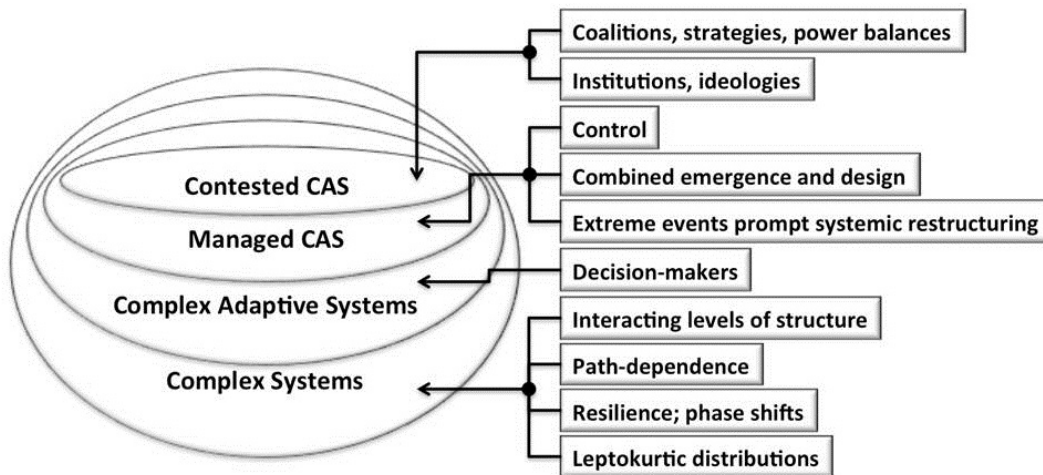


Figure 1: Classes of complex systems. For further explanation see main text.

105 All ecosystems can be classified as *Complex Systems* (the outermost ellipse), i.e., systems in
106 which system components interact to generate emergent behaviour that cannot be adequately
107 understood without the description of intermediate, interacting levels of structure. Complex
108 systems generally display the additional features listed in Fig. 1:

- 109 • path-dependence (events at one time can determine or constrain the state of the system
110 for an indefinitely long period);
- 111 • resilience and phase shifts: the system has two or more relatively stable states, tending to
112 remain in one such state until internal or external pressures reach a certain tipping point,
113 when it switches rather quickly into another state (Holling, 1973; Bitterman and Bennett,
114 2016);
- 115 • leptokurtic (fat-tailed) distributions of the size of system disturbances: while large dis-
116 turbances are less common than small ones, their numbers tail off more slowly than an
117 exponential distribution (Zurlini et al., 2006).

118 All ecosystems are also *Complex Adaptive Systems* (CAS; the next ellipse, (Holland, 1992)),
119 meaning that they include interacting decision-making components: actors, or agents, the term
120 we use here. Some of an agent’s decisions at least can affect its survival, or some other measure
121 of success, such as inclusive fitness, wealth, or happiness. Agents can adapt through evolution or
122 learning. Their decisions may be based on some form of cognitive processing, as with humans,
123 other social animals, human collectives (such as households, firms or governments) or even human
124 artefacts (such as robots or pieces of software); or be simply reactive – perennial plants, for
125 example, may “decide” whether to flower in a given year, depending on the weather and their
126 stored resources.

127 The difficulty of modelling a CAS has additional dimensions beyond those of complex systems
128 lacking agents, in that adaptive behaviours and interactions between the decisions of multiple
129 agents have to be considered, as does agent diversity. Of course a CAS may be modelled with-
130 out including these aspects, but the modeller should be aware of them. CASs can be further
131 differentiated according to the range of capabilities displayed by the agents acting within them,
132 as described below.

133 *Managed CASs* or MCASs (next ellipse) form a subset of CASs, in which at least one agent is
134 able to assess and attempt to regulate the system at a non-local level. Many SESs are MCASs.
135 In an MCAS, global events and structures may, as in any complex system, emerge from the
136 aggregate of local interactions among components, without any agent intending it – a feature
137 that is frequently stressed in the literature on system complexity; but such events and structures
138 may also be modified, controlled or designed by one or more agents, perhaps using external
139 symbol systems such as written plans, blueprints and charts. Notably, extreme events (such as
140 an ecological catastrophe or stock-market crash) may prompt such agents to undertake restruc-
141 turing of the system, to recover from (or take advantage of) the extreme event, and prevent (or
142 encourage) a recurrence. The capacity of actors to change a system deliberately to create a new
143 organization is commonly referred to in the literature as “transformability” (Folke et al., 2010;
144 van Apeldoorn et al., 2011). Modelling MCASs adequately requires ways to represent agents
145 themselves capable of representing at least some non-local aspects of the system, and their own
146 actions, and of planning. However, it is possible to model some aspects of such sophisticated
147 agents without attempting to simulate them in full – such a full simulation being an unsolved
148 problem in artificial intelligence.

149 Finally, *contested CASs* or CCASs (innermost ellipse) are MCASs that include multiple (in-
150 influential) agents that can come into conflict because of differing goals. Many SESs fall into this
151 category, including all sufficiently large ones. Here, strategic considerations come into play, and

152 the mathematics of non-cooperative game theory, and the areas of artificial intelligence used in
153 the design of game-playing programs become relevant. Work on social dilemmas, cooperation
154 and altruism is also of significance here, and there is already a considerable amount of work on
155 these topics that can be drawn on, including in the agent-based modelling field (Gotts et al.,
156 2003; van Lange et al., 2013). Additional complexity comes from the diverse types of interactions
157 between competing strategic agents. For example, ten Broeke et al. (2018) (this issue) present a
158 suite of models in which different agents cooperate or defect in their interactions, which affects
159 the resilience properties of the system as a whole. It is fair to say that wholly adequate ways to
160 model CCASs are likely to be a long way off, but again, it is possible to model some aspects of
161 strategic interactions.

162 In addition to being highly complex, all SESs are *open*, in the sense that factors operating
163 from outside the SES have significant causal influence. This raises a significant issue for vali-
164 dation in models of SESs (Oreskes et al., 1994). It also raises questions of where to draw the
165 system boundary when conceptualizing the empirical world (Hofstede, 1995). Sometimes mod-
166 elling pragmatics mean that feedback loops involving “slow” variables (Carpenter and Turner,
167 2001; Crépin, 2007; Walker et al., 2012) are ignored because their effects are negligible over the
168 model’s time-frame; we could expect agreement in modelling communities that this is appropri-
169 ate. However, decisions about whether to include phenomena, and if so, whether to do so as
170 endogenous, or as exogenous driving variables, are also based on more context-specific criteria:
171 the availability of data, or considerations of “elegance” or feasibility and tractability of analysis
172 in the chosen modelling approach. Here, a consensus is less obviously achievable.

173 There is a further complication to beware of in designing a model of a CCAS: stakeholders
174 will generally attribute perceptions and goals to *each other* – but these will often be, at least
175 in part, misrepresentations, deliberate or otherwise (Milner-Gulland, 2011). The very fact that
176 stakeholders with opposing views and interests tend to misunderstand and misrepresent each
177 other is a key part of the difficulty of SES modelling. The approach of participatory modelling
178 (discussed in section 3.3) is relevant here.

179 2.2. Terminology, indicators and models

180 As scientists, we want to understand SES dynamics; as policy-makers or concerned citizens we
181 want to preserve or improve them, and hence need to assess their current state, and how it is
182 changing in relation to those goals. Many contemporary assessments of SESs revolve around the
183 concepts “resilience”, “sustainability” and “ecosystem health”. These concepts are ill-defined
184 and contested, due both to the fact that different fields of application require different concepts,
185 and to the independent development of these ideas in different disciplines (Janssen et al., 2006;
186 Redman, 2014; Fleurbaey, 2015).

187 Resilience (in the ecological sense) refers to the capacity of an ecosystem (or socio-ecosystem)
188 to maintain structure, function and feedbacks in the face of disturbance (Folke et al., 2010),
189 but the state maintained may be judged desirable, undesirable or neither. Resilience needs to
190 be evaluated as “resilience of what, to what?” (Carpenter et al., 2001), as not all pressures
191 affect SESs in a similar fashion. The closely related “tipping point” concept emerged from the
192 realization that an ecosystem could have more than one stable state, or “basin of attraction”,
193 and that internal or external disturbances could shift it between basins. The disturbance may
194 simply be a gradual change in some variable – such as the amount of a nutrient available. A lake
195 may shift rapidly from an “oligotrophic” (low-nutrient) state, with clear water and oxygen levels
196 high, to a “eutrophic” one, in which algal growth makes it opaque and reduces oxygen levels,
197 as dissolved nutrient levels rise. Nutrient levels may then need to fall considerably below the
198 threshold at which the switch occurred in order to switch it back – the phenomenon of hysteresis

199 (Scheffer et al., 2001, 2009, 2012).

200 Ecosystem health is frequently defined in terms of the absence of toxins; the roster of species
201 present relative to what would be expected; and the ecosystem’s ability to recycle waste products.
202 However, for a socio-ecosystem, the welfare of the human inhabitants must also be considered
203 (Costanza, 2012; Lu et al., 2015; O’Brien et al., 2016); and speaking of a system’s “health” is in
204 any case best regarded as metaphorical, as ecosystems are not organisms, and what kills some
205 components of an ecosystem may (generally, will) encourage others to flourish.

206 Finally, the idea of sustainability is linked to human use of the environment, without dam-
207 aging it in ways that undermine its ability to provide ecosystem services: clean air and water,
208 flood control, recreation, etc. There is, however, extensive argument about what constitutes
209 sustainability, and even whether it is a meaningful term, particularly in combinations such as
210 “sustainable growth”, widely regarded as self-contradictory (Bell and Morse, 2008; Bjørn et al.,
211 2015; Sarvajayakesavalu, 2015).

212 Lack of agreement about how to operationalize the above concepts makes measuring them
213 hard, but more fundamentally, the systemic complexity of CCASs and MCASs makes it inherently
214 difficult to develop simple measures for them. Certain measures may serve as indicators, just as
215 temperature may be an indicator of the health of an individual. Indeed, many indicators have
216 been proposed; a distinction can be made between ecological indicators, i.e., indicators regarding
217 the ecological side of SESs, social indicators, those regarding the social side, and socio-ecological
218 indicators, those relevant to both. However, such indicators will usually not show a one-to-one
219 correlation with emergent SES properties, because they only touch on single facets of the SES –
220 much as temperature is an indicator of fever, but not all aspects of human health are correlated
221 with temperature.

222 Ecological indicators include physical quantities (temperatures, light levels, hydrological mea-
223 surements, concentrations of chemical species), biophysical measures (biomass, respiration, detritus),
224 species abundance and biodiversity, network measures (food webs, trophic levels, biophysical
225 measures at different trophic levels), maximum disturbance from which recovery is possible, and
226 time to recovery (Siddig et al., 2015; González et al., 2016). Social indicators include individ-
227 ual health and well-being, social capital, and measures of inequality, trust and social cohesion,
228 crime and violence, misuse of alcohol and other drugs, and family structure and functioning
229 (Abbott and Wallace, 2012; Jacob et al., 2013; Klomp and de Haan, 2013; Hicks et al., 2016). Fi-
230 nally, socio-ecological indicators include thermodynamic measures (from “ecological economics”),
231 “footprint” measures, sustainability indicators, and assessments of system resilience, ecosystem
232 services and resource efficiency (Coscieme et al., 2013; Estoque and Murayama, 2014; Li et al.,
233 2014; Lu et al., 2015; Banos-González et al., 2015, 2016; Eisenmenger et al., 2016; Recanatani
234 et al., 2016).

235 The very range and variety of indicators makes SES assessment a problematic business.
236 Modelling can guide the choice of indicators for specific assessment purposes. Models represent
237 codified, integrated system knowledge, and can be used to “grow” emergent properties, explore
238 scenarios, and identify distributions of outcomes. However, SES modelling faces at least two
239 major challenges deriving from the intrinsic properties of the systems concerned:

- 240 1. It is difficult to untangle the webs of interactions at various spatial, temporal and or-
241 ganizational scales sufficiently to draw a system boundary. There is a trade-off between
242 including too much detail, with the resulting model having too many parameters to feasibly
243 calibrate it or explore its dynamics, or too little detail, oversimplifying. The kinds of dy-
244 namics associated with complex systems, discussed above, make data difficult to replicate,
245 with the result that models are left simulating “stylized facts” or “patterns” (Grimm et al.,
246 2005) rather than conforming to data validation criteria associated with traditional sta-
247 tistical measures of model performance. That, and typically limited access to data, mean

248 confidence in model predictions is difficult to establish.

249 2. Many SESs, as noted above, are Contested Complex Adaptive Systems: they include agents
250 capable of thinking about the dynamics of the system as a whole, but differing among
251 themselves over just what those dynamics are, and how, if at all, they should be changed.
252 Typically, at least in cases where a CCAS is contemporary rather than historical, the
253 modeller will be confronted with choices which have political implications: if they adopt
254 the viewpoint favoured by one agent or group of agents, they will quite reasonably be
255 perceived as siding with that agent or agents. Such political implications of modelling
256 choices may occur with respect to historical systems, and indeed to systems other than
257 CCASs, but they are at their most stark for contemporary CCASs. Issues that confront
258 researchers or policy-makers with such clashes between stakeholders (see also section 3.3)
259 are sometimes referred to as “wicked” (Churchman, 1967).

260 3. Choosing SES modelling methods

261 An SES model, in the broadest sense, is anything that is used to understand a real-world SES
262 through some (real or supposed) resemblance between them. Models can be constructed in
263 different ways, have different requirements for data and relationships to theory, and be used for
264 different purposes. This section discusses these matters.

265 3.1. Availability of data and theory

266 The ecological aspect of SES modelling is by no means simple, given the sheer number and variety
267 of organisms living just on and below a square meter of grassland or woodland, but as argued
268 above, it is the social aspect that is most in need of development. Yet data collection on human
269 decision-making and social networks, and their effects on SESs, is frequently given far less in the
270 way of attention and resources than collection of data from the biophysical environment.

271 In addition, there are practical limits to data acquisition. One limitation results from scale
272 mismatches (e.g. feedback responses to human decision-making typically occur on a much slower
273 time-scale and much larger spatial scale than that of the human decision-making itself, as in the
274 case of climate change). Another is the difficulty of extracting reliable data from observations
275 about human behaviour (e.g. people often do not accurately reveal their motivations for doing
276 things, even when they intend to). Again, data on social networks and the interactions taking
277 place within them, and longitudinal data, are often far from adequate.

278 Hence, in modelling an SES there are often no good data about at least some of the human
279 elements one wishes to include. This does not always invalidate the modelling effort. In the
280 absence of data for a specific element of the model, one can work with estimates, backed up
281 by theory. If an appropriate theory is used, one could for instance show potential emergent
282 behaviours or tipping points that could happen if certain future developments occurred. De-
283 termining what data and/or theory to base the model on is therefore an important step in its
284 own right, and one that is linked to the choice of modelling goals and scope. Within psychology
285 and the social sciences, there are abundant theories which are sufficiently articulated to form the
286 basis of a model of a social system, and it is sometimes possible to apply them to SES modelling
287 (Jager et al., 2000; Hofstede, 2017). Conversely, designing and implementing models can assist
288 theory development (Zellner et al., 2014).

289 However, there are certainly difficulties with this approach. Theories of human behaviour and
290 decision-making are scattered across psychology and the social sciences, most of them focus on
291 isolated aspects of these multifaceted phenomena, they often lack a clear causal basis (Schlüter

292 et al., 2017), and frequently leave unstated many details which must be specified for a working
293 simulation (Polhill and Gotts, 2017). Moreover, there is still no generally accepted framework for
294 dealing with key social concepts such as values and norms (Chan et al., 2012), because the social
295 sciences remain methodologically contested disciplines. Thus, the inclusion of human behaviour
296 and decision-making in SES models can require making many assumptions about the relevant
297 actors (Müller-Hansen et al., 2017), even when some support is available from theory.

298 3.2. Modelling aims

299 There are many different kinds of purpose for a model and these are not always distinguished. We
300 focus here on five principle kinds: prediction, explanation, theoretical exploration, illustration
301 and analogy (or a way of thinking about things). For more about different modelling purposes
302 and their implications, see Edmonds (2017).

303 The essence of **prediction** is anticipating aspects of unknown data before they are known.
304 Once a predictive model has been tried on multiple different cases and different conditions suc-
305 cessfully one can start to rely upon it. Developing a model for prediction can be quite different
306 from building one for other purposes (Silver, 2012). The gas laws are a simple case of a predictive
307 model – which does not, and need not, explain why it works in order to predict. An example of
308 a predictive social model is Nate Silver’s model of the US presidential elections (Silver, 2016).
309 This does not predict a specific result but rather the probability distribution of outcomes, so its
310 accuracy can only be assessed by considering multiple cases (different years, or the results in the
311 various states in a single year, for example). Of course, this approach is not specific to social
312 models.

313 The second kind of purpose is supporting an **explanation** – showing how a set of plausible
314 mechanisms might produce outcomes that match some known data (in some well-defined way).
315 If it succeeds, then the workings of the model explain the outcomes (or at least certain aspects
316 of the outcomes). We can test our understanding of the mechanisms with experiments on the
317 model. A typical example of an explanatory model is the Fitzhugh-Nagumo model for spiking
318 neurons (FitzHugh, 1955; Nagumo et al., 1962), which gives no predictions of the membrane
319 potential of neural cells at all but simply illustrates how a spike in this potential develops. Many
320 ABMs and the very similar individual-based models (IBMs) in ecology are aimed at explanation,
321 trying to explain emergent system properties from micro-level processes (Macal and North, 2005;
322 Grimm and Railsback, 2012).

323 Both prediction and explanation are empirical uses of models: the connection between the
324 model parameters, mechanisms and outcomes should be well-defined and verifiable. However
325 they are very different. The workings of a predictive model do not have to be plausible; it just
326 has to predict successfully. The workings of an explanatory model are the constituents of the
327 explanation that results; if the workings are implausible so is the explanation. It is a mark of
328 mature science when we know how predictive and explanatory models relate so we know why
329 predictions work but often in science one kind of model is developed before the other. For
330 example, the gas laws were discovered before we knew why they worked (random gas molecules
331 bouncing around) while Darwin’s explanatory theory of evolution was discovered before any
332 predictions from genetics were possible.

333 The remaining purposes are not empirical. **Theoretical exploration** or exposition takes a
334 set of mechanisms and tries to understand the resulting system properties in terms of some theory.
335 If the mathematics is analytically solvable one might obtain a general solution – which may be
336 possible for some models of ordinary or partial differential equations, such as the logistic growth
337 model and the heat equation (Kot, 2001), but in more complicated cases one might just have to
338 calculate or simulate the outcomes, exploring the space of outcomes as thoroughly as is feasible,

339 and testing any theoretically-derived hypotheses about the overall behaviour. For example, a
340 “minimal” model of agents harvesting a renewable and diffusing common-pool resource has been
341 used to study the effects of natural selection (ten Broeke et al., 2017) and cooperation (ten
342 Broeke et al., 2018) (this issue) on resilience, using sensitivity analysis to identify contributing
343 factors. Theoretical models do not tell us how observed reality is; to show that a set of theoretical
344 results holds for what is observed, we would then have to establish this as also an explanatory or
345 predictive model. More usually, the theory is not straightforwardly applied, but forms the core
346 of a more extensive model.

347 **Illustrative** use of a model just aims to show an idea or particular case. Axelrod’s “evolution
348 of cooperation” models (Axelrod, 1984) did not give a general outline of cooperative behaviour
349 in formal games, but did illustrate how cooperation might evolve. The purpose of illustration is
350 to be clear, so illustrative models tend to be simple, but may not meet the rigorous standards of
351 theoretical exposition (and might turn out to capture a vanishingly special case, for example).

352 A fifth case is to use a model as an **analogy** – as a way of thinking about things. This is not
353 empirical, because how it relates to what we observe will change with each case it is applied to
354 in a flexible and creative manner. Analogies, whether verbal, visual or encapsulated in a formal
355 model are essential for thinking. We need them to guide the direction of our efforts, they might
356 suggest new hypotheses but they are not reliable pictures of the world.

357 Illustrative and analogical models are frequently used as a tool for either communication
358 or negotiation (a *boundary object*). In the case of communication the model is designed to
359 encapsulate a point that someone wants others to understand. Models can be very useful to
360 communicate examples that are too complex to be adequately described using other mechanisms –
361 because the recipient can then play with the model gaining rich experience about the interactions,
362 emergence and dynamics. A more complicated use is where a model is used to develop a shared
363 representation or a vehicle for discussing issues in common. In this case the emphasis is not
364 so much on representing an independent phenomenon but rather on its coherence with the
365 stakeholders’ perceptions of the issue or situation. See Cash et al. (2003), and for a survey of
366 this kind of use of models Barreteau et al. (2013).

367 3.3. The system under-determines the model

368 As we have shown, modellers need to consider multiple factors aside from the nature of the
369 real-world systems or class of systems they intend to model (Kelly et al., 2013). These include
370 (but are not limited to):

- 371 • What is the purpose of the model?
- 372 • What type of data is needed for the development of the model?
- 373 • How much data is available for the model?
- 374 • What theories are available for use in constructing or constraining the model?
- 375 • Who are the model users? Researchers, policy makers, or stakeholders?

376 All these considerations can influence the best boundaries of the model in regard to content (e.g.
377 which classes, variables and relationships to include and which not), and spatial and temporal
378 scales.

379 So in general the system under-determines what model, and indeed, what type of model,
380 would be the right outcome of a modelling process. The best answer may be: “No model”, at
381 least as far as models in software are concerned, if the requirements stemming from the purpose

382 of the model – in terms of data available, theoretical basis, stakeholder involvement and so on –
383 cannot be met. The possibility also arises that multiple models, perhaps of different types, may
384 be needed to achieve the modellers’ goals. Each model may then serve a different purpose.

385 We recommend thinking primarily in terms of *modelling projects*, rather than individual
386 models – see Fulton et al. (2015) and Forrester et al. (2014) for examples of such an approach.
387 A modelling project is an investigation of a specific system (in our case, an SES) or group
388 of systems, in which the design, construction and use of software models is intended to play an
389 important part. It may involve the construction of a number of such models, and in addition, will
390 typically include data collection, theoretical analysis, and in many cases stakeholder involvement.
391 Different models within a project may adopt different modelling methods. They may also adopt
392 different theoretical viewpoints, e.g. there may be a more economically oriented model that
393 assumes all agents behave according to economic rationality, and a socially oriented model that
394 assumes irrational behaviour among agents. Moreover, since in SESs the usual state of affairs
395 is that many stakeholders are involved, and the various stakeholders typically have different
396 views of the system and preferred system states (the system is a CCAS), the modeller may find
397 it useful to produce different simulation models to reflect the viewpoints of different groups of
398 stakeholders.

399 Those who live their lives in an SES may be the most knowledgeable about it. This makes
400 it desirable to obtain local stakeholder collaboration in model design and refinement. Also, if
401 stakeholders disagree on desirable outputs, or on feasible interventions, a model created without
402 the contribution of certain stakeholders or groups, may be cursorily dismissed by them. So, there
403 are two good reasons for involving stakeholders at model development time: system knowledge,
404 and model acceptance. This has been recognized by SES researchers, and it has given rise to the
405 stream of stakeholder-involving ABM-based research known as companion modelling (Etienne,
406 2014) or participatory modelling (Voinov et al., 2016). Allison et al. (2018) add a third reason:
407 preventing models being regarded as predictive oracles, contrary to the intentions of the modellers
408 themselves: if stakeholders are involved in designing the models, they may have a better grasp
409 of their limitations, and this message can be reinforced by the modellers.

410 Nevertheless, these approaches have their own pitfalls. Stakeholders are rarely used to think-
411 ing in terms of abstract models, so they require modellers skilled in communication, who build
412 models with understandable interfaces. The modellers must also be able to work effectively in
413 situations involving disagreement, competition for their attention and approval, and conflict.
414 Seidl (2015) argues that there is often insufficient reflection on the processes of participation,
415 and recommends the use of common project protocols or templates, both to facilitate project
416 planning and to improve resulting publications. Stakeholders are, almost by definition, biased:
417 they have a stake in seeing the system in certain ways, ways which justify their own actions.
418 Voinov et al. (2016) note that: “Participatory processes need mechanisms to explicitly recognize
419 human biases and heuristics (i.e. mental shortcuts) when they occur, and to resolve them or
420 compensate for them if needed.”, and give a number of recommendations for such mechanisms,
421 including getting a diverse group of participants, and using “structured, accountable, traceable,
422 transparent processes” at all stages of the modelling process. Yet as Barnaud et al. (2005) de-
423 scribe, it is extremely difficult to ensure that those who are at the bottom of social hierarchies
424 (the poor, women, members of ethnic minorities) are able to voice their viewpoints, and the
425 source of unsustainable practices in an SES may lie with national authorities, or others remote
426 from the SES being modelled. Participatory approaches are often valuable, but no panacea.

427 3.4. Approaches to modelling

428 At the most general level, we can divide modelling into conceptual, statistical, mathematical and
429 simulation modelling.

- 430 • **Conceptual modelling** examples include fuzzy cognitive maps, conceptual mapping and
431 causal loop diagrams, but they may consist solely of natural language descriptions. A
432 major advantage of graphically encoded conceptual models is that they are a good com-
433 munication tool; they can be discussed with other researchers and stakeholders without
434 a modelling background. A major disadvantage is that they cannot be unambiguously
435 applied to observed systems, but always involve some amount of interpretation when thus
436 applied.
- 437 • **Statistical modelling** is used for understanding correlation between variables. Examples
438 include Monte Carlo, Bayesian networks, regression models, and structural equation mod-
439 elling. There are two basic kinds of statistical model: descriptive and generative (Ng and
440 Jordan, 2002). A descriptive model abstracts certain properties from a set of data, to give
441 insights into that data or allow different sets of data to be compared. Generative models
442 allow for projections from the data to be made. Usually statistical modelling is used in a
443 descriptive manner for SESs.
- 444 • **Mathematical modelling** is generally associated with theoretically focused models. Most
445 examples are comprised of differential equations, see for example Kuehn et al. (2013).
446 General conclusions can sometimes be analytically derived for these kinds of model, allowing
447 a near complete characterisation of their behaviour. Due to SES complexity, mathematical
448 models tend to be considerably abstracted from any observed target SES.
- 449 • **Simulation modelling** is used when the outcomes of a system cannot be derived ana-
450 lytically, but rather each example scenario needs to be computed individually. They may
451 also be used to improve transparency and comprehensibility in contexts where those with
452 an interest in the model do not understand analytical derivations. Simulation models will
453 typically include adjustable parameters and stochastic elements, and be run many times,
454 producing a range of results. Statistical methods may be applied to this range, and sensi-
455 tivity testing may be used to determine the effect of changing specific parameters.

456 Conceptual modelling is always part of the modelling process, but on its own, is insufficient for
457 prediction, explanation, or theoretical exploration of complex systems such as SESs. Statistical
458 modelling approaches are very data-driven and typically assume a static system structure. They
459 are not suitable for understanding emergent properties, which is clearly relevant when SESs
460 are concerned. Mathematical models are explicitly dynamical. However, only models of very
461 limited complexity (in terms of number of state variables, parameters, stochastic and/or spatial
462 components, and types of feedback included) are analytically tractable, and these are mainly
463 suited to serve as caricatures of reality.

464 Simulation modelling allows for the inclusion of multiple state variables, many parameters,
465 stochastic and/or spatial components, and several feedback mechanisms. Simulations can be
466 based on a system dynamics, cellular automaton or agent-based model approach, or on combi-
467 nations of these.

468 Systems dynamics (SD) is commonly used to describe biogeophysical processes, including
469 population, groundwater, and nutrient flow dynamics. SD models are based on a mean field
470 approximation of state variables at an aggregated level. They usually represent a combination of
471 a mathematically explicit description of processes, such as differential equations, and simulation

472 using a numerical implementation. A major advantage of SD models is that there are many
473 model analysis methodologies available, including methods that can be used to address concepts
474 such as tipping points and resilience. Major drawbacks are that these models do not allow for
475 lower-level descriptions and handle social processes poorly.

476 Cellular automata models are frequently used in areas such as land use change prediction
477 and policy (Yang et al., 2014). In these spatially explicit models, each “cell” has a number of
478 possible states, and in a pure cellular automaton model, the state of a cell at time $t + 1$ depends
479 only on its own state and those of a limited set of neighbours at time t . Such land use change
480 models can be very useful predictive tools, but abstract away the agency of actual land managers,
481 and also impose a fixed spatial structure and set of possible land uses, which take no account
482 of changes in ownership or management, or of land use options. Cellular automata simulations
483 involving commons dilemmas go back to the 1980’s, e.g. Axelrod (1984), Nowak and Sigmund
484 (1992), but these focus mainly on the development of optimal or idealised strategies and not on
485 actors’ external drivers and internal motivations. In other words, people seldom behave in these
486 idealized ways, which necessitates the inclusion of theory regarding what internally motivates
487 and externally drives people’s decisions.

488 Agent-based modelling is an approach in which decision-makers (agents) of some kind are
489 explicitly represented. Their decisions generally affect both the relative success and inter-
490 relationships of the agents themselves, and the environment in which they are placed. The
491 agents may represent individuals, households, firms, states or other collectives, and typically
492 can differ from each other in terms of motivation, abilities or powers, and knowledge. An ABM
493 may well include System Dynamics and/or Cellular Automaton elements representing aspects of
494 the agents’ environment (Gaube et al., 2009; Haase et al., 2012; Martin and Schlüter, 2015) or
495 governing the agents’ internal processes (Bradhurst et al., 2015; Schieritz and Größler, 2003).

496 Ideally, there would be a clear set of guidelines providing a universally-agreed specification
497 of the appropriate modelling approach to use based solely on attributes of the empirical world,
498 modelling aims, and the data available. The choice of modelling approach, however, is often more
499 a question of disciplinary norms and individual preferences than of rigorous analysis of criteria.
500 Kelly et al. (2013) do provide a decision tree to guide the choice of modelling approach based
501 on the mix of qualitative and quantitative data available, and availability of existing models
502 for processes and system components; but the tree’s decision nodes also require evaluation of
503 modelling purpose, the perceived importance of feedbacks, and the interests of the modeller.
504 Other reviews of modelling approaches are rather less prescriptive. Schlüter et al. (2012) do
505 not make specific recommendations about which approach to use, but instead propose using
506 Ostrom’s framework (Ostrom, 2007, 2009) as a basis for justifying modelling choices and making
507 comparisons among various models conceptualising SESs.

508 A model of a complex system, and in particular of an SES, can range from very simple to
509 highly complicated (where “complicated” means “consisting of many components of different
510 types”). Other things being equal, a simpler model is to be preferred. When a model gets more
511 complicated or complex three major drawbacks start to play an increasing role:

- 512 1. The model may become over-fitted, i.e., it starts to fit noise which reduces its applicability
513 for other datasets. If there are more free parameters in the model than can be calibrated
514 using the available data, then an explanatory model may be too easy to fit to the data –
515 the ‘wobble room’ to fit anything is just too great. Thus the fact that a model fits particular
516 data may not be significant.
- 517 2. Limitations in available computational power to run the model can prevent appropriate,
518 adequate exploration of the model.
- 519 3. It becomes harder to understand how the model functions.

520 Furthermore, more complexity does not necessarily mean that the model is more accurate
521 (Blair and Buytaert, 2016). For the purposes of analogy, a simple model may give more insights
522 than a more complex one; if one aims at illustration, then no more is needed than the minimum
523 of structure and processes to show what is intended. Similarly, for the exposition of theory, one
524 would want to pare down all but the mechanisms of interest.

525 If a model has a predictive purpose, then it may be possible to feed enough data through it
526 to reveal any patterns, which can then be used to predict new observations. In SESs, however,
527 prediction is rare given the complexity of the systems and the relative paucity of data. Most
528 models of SESs tend to be aimed at least in large part at explanation, to deepen understanding
529 of the system or class of systems modelled in terms of a set of plausible mechanisms.

530 As mentioned above, a modelling project may need to include multiple simulation models of
531 a single system. One more way in which this may be useful arises out of the problems intrinsic
532 to complex models: constructing different models to represent different levels of granularity or of
533 abstraction. A good explanatory model might be very complex, especially if it integrates both
534 social and ecological aspects. It may then be necessary to construct a model of this model (a
535 metamodel), in order to examine some of the mechanisms involved in a more analytic manner.
536 This theoretical model can then be related to the explanatory model in testable and well-defined
537 ways, gaining some of the benefit of both (Lafuerza et al., 2016).

538 4. Agent-Based Modelling of SESs

539 4.1. Advantages of agent-based modelling of SESs

540 Modelling aimed at explanation of a system's dynamics in terms of underlying mechanisms
541 requires the model to represent these mechanisms adequately and that means representing them
542 explicitly. Such models necessarily attempt some structural correspondence to a part of the
543 observed and/or conceptualised external world. The question then arises of how much structure
544 and which processes need to be represented in the model. We always have limited resources
545 of time, computation and understanding, so some compromise in terms of a model's faithful
546 representation of the modelled system is almost always necessary (Grimm et al., 2005). However,
547 if a model is too simple, it is likely to omit features of crucial importance. For an SES, these
548 features include the decisions, actions and intentions of human individuals, along with their
549 institutions, knowledge, beliefs, resources and technologies. Schlüter et al. (2012) emphasize
550 coevolutionary processes and micro-level decision-making, while Filatova et al. (2016) stress the
551 kinds of feedback within and between the social and ecological subsystems, links between various
552 organisational scales, and the representation of nonlinear behaviour.

553 These factors are demonstrably important in real-world SESs. We consider that Agent-Based
554 Models have the potential to capture far more of these key features than any other current
555 approach to SES simulation. They allow for detailed description of heterogeneous individual
556 actors' behaviour, which SD models cannot do, and can generate emergent properties, as the
557 interactions of agents with each other and their environment produce macro-level patterns such
558 as directional or cyclical change, and greater or lesser system resilience. In contrast to typical
559 cellular automata, these macro-level features can in turn be perceived by and influence the agents.
560 Moreover, unlike typical cellular automata agents, ABM agents may be given the power to move,
561 to acquire or lose ownership of or influence on specific parts of that environment, and to establish
562 links with agents other than immediate neighbours.

563 Another advantage is that ABMs lend themselves well to communicating model structure
564 and behaviour to stakeholders: people in general are used to thinking in terms of the intentions,
565 actions and interactions of both other individuals, and collectives such as households, firms, gov-

566 ernments and states. Most people are far less used to thinking in terms of differential equations,
567 or the kinds of dynamics typical of cellular automata.

568 In sum, it is the *expressivity* of ABMs that leads us to recommend their use. As we have
569 already noted, ABMs can include systems dynamics and/or cellular automata elements. An SES
570 typically links organisms of very different degrees of behavioural sophistication (such as plants
571 or bacteria on the one hand and farmers or gatherers on the other); and the less sophisticated in
572 particular may be present in very large numbers. Large numbers of comparatively simple agents
573 may be best represented using differential equations or cellular automata, even within a model in
574 which human beings (and possibly some other organisms) are represented as individual agents.

575 There are different ways to combine SD and ABM models, ranging from loosely coupled or
576 sequential, where the output of one model component is fed to the next, to fully integrated,
577 which incorporates feedbacks between the two (or more) components during a simulation run
578 (Swinerd and McNaught, 2012). Martin and Schlüter (2015) provide an example of the latter
579 (including a detailed procedure for achieving it) with their model of the restoration of a shallow
580 lake being polluted by untreated sewerage from private households. This SES case study links
581 an agent-based model of the social sub-system representing individual house owners and a local
582 authority with a system dynamics model of the ecological sub-system (the lake with two types
583 of fish in a predator-prey relationship). A somewhat similar example (FEARLUS-SPOMM, see
584 Polhill et al. (2013)) is examined in Appendix 1.

585 4.2. Drawbacks of agent-based modelling of SESs

586 The very expressivity of ABMs, however, is a source of significant drawbacks. Because every
587 agent can have its own individual properties, potentially different from those of all other agents
588 in the model, the number of tunable parameters of an ABM can become enormous, and indeed,
589 difficult to calculate, once we consider that the number of agents and the statistical distributions
590 of their properties and relationships with each other can themselves be model parameters. Given
591 enough parameters, it becomes difficult to establish that there is any set of outputs that could
592 not be produced. However, work is needed to establish the change in realizability of outputs
593 introduced by adding an agent to a model, and how this compares with adding a term to a
594 traditional model (Polhill and Salt, 2017). Of course, by no means all ABMs are intended as
595 empirical models of specific systems, but even for those that are not, the problem of defining the
596 range of acceptable outputs remains.

597 ABMs can also suffer from a lack of transparency in that it may be difficult to determine
598 (even for the modellers themselves) what specific features of the model represent in the system
599 or type of system being modelled – or indeed, whether they represent anything at all, rather
600 than simply being “scaffolding” necessary for the model to function as a piece of software, and
601 to allow the user to manipulate it. This problem is not unique to ABMs, but that it is a serious
602 issue is indicated by attempts at replication which show that altering seemingly minor aspects of
603 an ABM can radically change the results (Edmonds and Hales, 2003; Janssen, 2007). The lack of
604 this kind of transparency places greater emphasis on code sharing and documentation practice
605 (Edmonds and Polhill, 2015).

606 In modelling any complex adaptive system, and in particular in modelling SESs, we can be
607 effectively certain that our model will not include all the layers of intermediate structure, or all
608 the kinds of interaction between agents, which are relevant to the behaviour of the real-world
609 system being modelled; any model (not just those that are agent-based) will inevitably be partial
610 in this sense, but this partiality may not be evident to the model’s users, and is easily forgotten
611 by its developers.

612 To keep ourselves as honest as possible as modellers, we propose making as explicit as feasible

613 *what we have knowingly left out of our models.* (The qualifier “knowingly” is a necessary one;
614 given our very limited knowledge of SESs and their “components” (particularly, of people), we
615 can also be pretty certain that we are leaving out more than we are aware of.) “As explicit as
616 feasible” is an elastic term, and deliberately so. We know, as modellers, the pressure to produce a
617 model rapidly, and the space limitations and other constraints of journals and conference papers:
618 emphasising what your model does not cover may not assist you in getting published. But
619 there are now model repositories such as OpenABM¹, where model code and documentation can
620 be archived and made available to other researchers. This documentation should, we suggest,
621 include an explicit statement of the model’s known limitations, along with its purpose, data
622 requirements, theoretical basis (if any), and stakeholder involvement (if any). The ODD format
623 (Grimm et al., 2006, 2010) is helpful in putting together the necessary documentation for ABMs
624 – similar formats exist for other types of models. In section 4.3, however, we propose a somewhat
625 different although perhaps complementary approach, which we believe will also help in dealing
626 with the other drawbacks of ABMs due to their expressivity: the use of formal ontologies.

627 4.3. Ontologies for agent-based models

628 An ontology (in the sense relevant here) is a formal account of the entities considered to be
629 involved in some system or type of system, and the relationships between them (Gruber, 1993).
630 For example, considering farming land use, one might distinguish people, households, farms,
631 fields, animals and crops, and specific subtypes of these broad categories. In an ontology each
632 such concept is given an obvious and unique label, which is then used in defining some of the
633 relationships between them. Thus “people run businesses”; “farm businesses own farms”; “a
634 field is part of a farm”; “arable and grazing are types of land use”; and “each field has a land
635 use applied to it”. This is illustrated in the (much simplified) ontology depicted in Figure 2.

636 Ontologies are already in use in many areas of work, including ecosystems research. Up to
637 now, their main use in this area has been for data integration (Poelen et al., 2014; Coetzer
638 et al., 2017), including semi-automated processing of remote sensing data (Myers and Atkinson,
639 2013), rather than in simulation modelling. Usually an ABM (or any other software model of
640 an ecosystem or SES) is described in natural language, sometimes accompanied by tables and
641 diagrams, and possibly structured according to some protocol such as ODD (Grimm et al., 2006,
642 2010). The real world system, situation or scenario (or type of system, situation or scenario) the
643 model is intended to represent will also be described in some combination of natural language,
644 tables and diagrams. Particularly for non-specialists, ontologies cannot replace clear and well-
645 structured natural language descriptions of either models or modelling targets, but we believe
646 they are a promising “mediating formalism” (Gotts and Polhill, 2009) to assist in bridging the gap
647 between program code and natural language description, with major advantages in the process
648 of designing, implementing and assessing a simulation model:

- 649 • Formal ontologies can be used to constrain and check complex simulations. Complex
650 simulations have many degrees of freedom and ensuring a simulation is consistent with an
651 ontology helps constrain these degrees. In this way ontologies can be seen as an extension
652 of type-checking in programming languages which is well known to reduce programming
653 errors.
- 654 • There are often fundamental differences as to what types of entities and relationships
655 should or can usefully be distinguished in any particular system. Formalizing ontologies

¹<http://openabm.org>

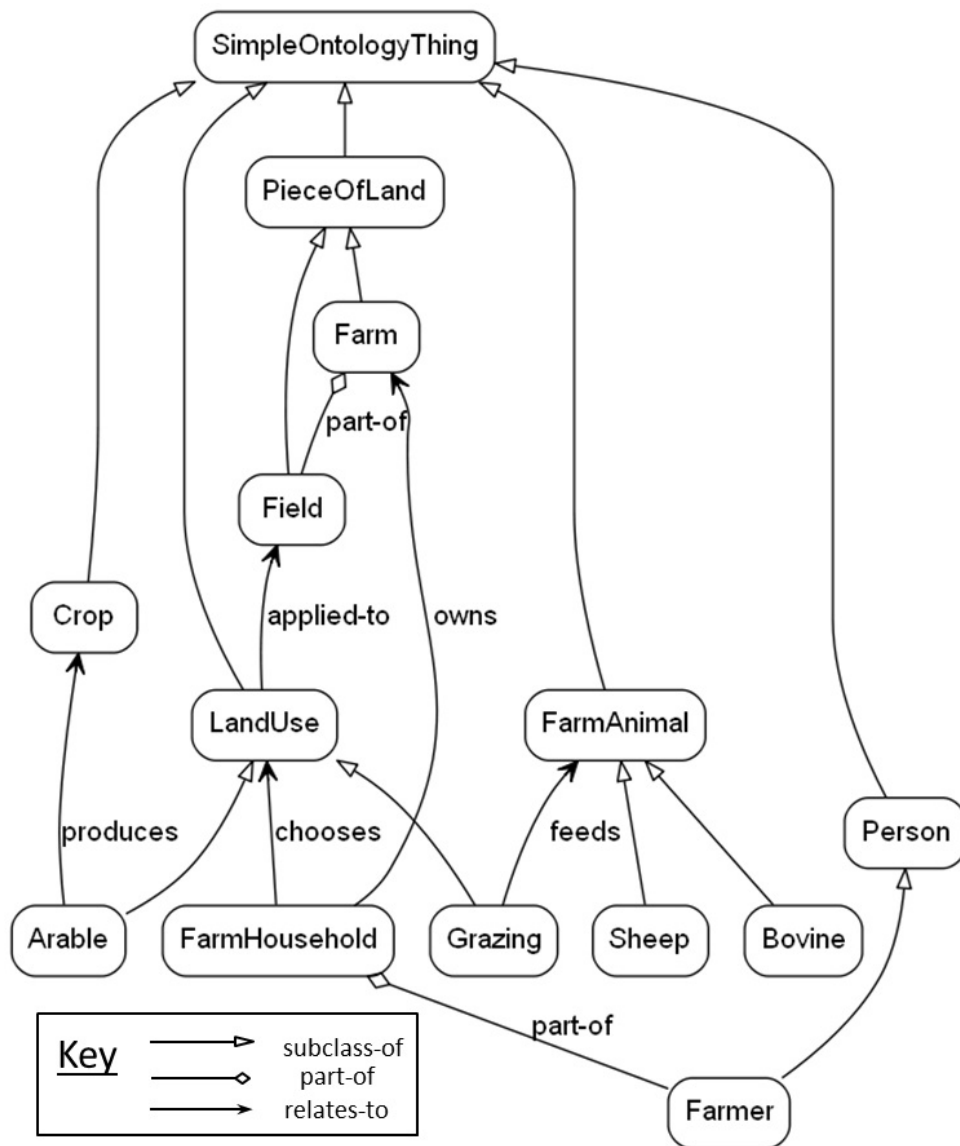


Figure 2: A Simple Ontology.

656 helps reveal these differences, which are often implicit. This is particularly important where
 657 there are experts from several disciplines, or multiple stakeholders, involved in a modelling
 658 project.

- 659 • Ontologies in diagrammatic form can also be useful in explaining the model to stakeholders
 660 and domain experts, although here, care is needed to present no more complexity than will
 661 be helpful to the intended audience.
- 662 • Polhill and Salt (2017) argue that for any complex model, showing that it can reproduce
 663 in its outputs the empirical measurements from the target system does not prove that it
 664 captures the underlying processes producing those measurements. They point out that a

665 neural network model, in which no attempt is made to capture such underlying processes,
666 can always be tuned to produce an arbitrary set of outputs if it has enough nodes. For any
667 kind of model which does aim to capture the mechanisms responsible for measured system
668 outputs, therefore, its ontological structure (its components and their interactions, whether
669 or not expressed in a formal ontology) must be considered in attempting to validate the
670 model. So if this structure was not specified as part of the model design process, it must be
671 derived from the model itself – Polhill (2015) shows how, for a particular software system
672 often used for ABMs (NetLogo, (Wilensky, 1999)), this process can be partially automated,
673 resulting in a formal ontology. Polhill and Salt (2017) suggest four ways in which such a
674 model-specific ontology can be validated: logical consistency; populating it with instances
675 from the modeled domain (if this proves difficult, it indicates that the ontology is not a
676 good fit); stakeholder and/or expert evaluation (by experts or stakeholders not involved
677 in the original design of the model or its accompanying ontology); and comparison with
678 existing ontologies.

679 • Ontologies can both be about a view of a system (making them a formalized kind of
680 conceptual model) and be applied to simulation models such as ABMs themselves. But
681 generally, the entities and relationships that exist within such a model are a subset of
682 those pertaining to the modellers’ conceptual model of the observed system. Thus when
683 simulating farming land use one might omit the people and conflate these with the farms,
684 thus to focus on what each farm household or business (as a unit) does with the fields
685 on its farm. As noted above, there will also typically be aspects of the simulation model
686 that have no direct counterpart in the system modelled, but are necessary to the model’s
687 operation or helpful for the user. The use of ontologies can help to keep the relationships
688 between the simulation model and the system clear, primarily for the modellers themselves.
689 This advantage is discussed in more detail below.

690 While the most human-accessible representation of ontologies is in diagrams such as Figure 2
691 they are fully expressed for computational purposes in languages designed for the task, the most
692 common of which is OWL (Cuenca Grau et al., 2008; Horrocks et al., 2003). OWL and similar
693 languages are in turn based on *description logics* (Baader et al., 2017), formal systems which aim
694 to maximise expressivity while retaining desirable computational properties such as decidability
695 (which guarantees that the process of determining whether or not a statement in the logic follows
696 from a given set of premises will be finite). Software exists for OWL ontology construction and
697 display (Horridge, 2011), for checking that ontologies are well-formed (Tsarkov and Horrocks,
698 2006; Sirin et al., 2007; Shearer et al., 2008; Bagosi et al., 2014) and for comparison (structural
699 matching) between ontologies (Faria et al., 2013; Hu and Qu, 2008).

700 The hierarchy of concepts in an ontology will often be a “tangled hierarchy”, where a concept
701 may have multiple links to superiors (sheep are ruminants as well as farm animals). An ontology
702 may or may not include specific instances of its classes. If it does, it may also include relationships
703 between these instances: an ontology could specify that Paris is the capital of France, for example.
704 The possible relationships between instances of concepts may themselves also form a tangled
705 hierarchy, which is part of the ontology. Since relationships represented in ontologies may be
706 spatio-temporal, an ontology can encode a spatial layout, or a scenario taking place over time
707 (Gotts and Polhill, 2009).

708 Ontologies have been used in conjunction with multiple models within a modelling project
709 (not, as it happens, including ABM) in agricultural systems research (Janssen et al., 2011), and in
710 conjunction with integrated assessment models (de Vos et al., 2010). Although de Vos et al. (2010)
711 focus on systems dynamics models, they raise the issues of model validation and transparency
712 noted in section 4.2 as difficulties encountered in using and assessing ABMs. Neither Janssen et al.

713 (2011) nor de Vos et al. (2010), however, use ontologies to clarify how the software ABM relates to
714 the system it attempts to capture, as proposed here: their ontologies aim to capture the structure
715 of a software model or set of connected models, while leaving the conceptual model to be described
716 only in natural language. Beck et al. (2010), in contrast, describe a software environment for
717 constructing systems dynamics models from ontologies in the agricultural domain. However, we
718 cannot find subsequent examples of work within this environment.

719 Here, we propose a somewhat different approach, with the focus on maintaining clarity and
720 transparency in modelling projects that may involve multiple models and multiple modelled
721 systems. In order to specify which aspects of the real world are represented (and which not) in
722 a simulation model, and how, we propose the use of several linked formal ontologies, drawing on
723 ideas from Polhill and Gotts (2006), Polhill and Gotts (2009) and Gotts and Polhill (2009), but
724 adapted to deal with the issues discussed in this paper.

725 Formal ontologies only encode the structural relationships between the concepts (and maybe
726 individuals) represented – this is all they can do. For example, if an ontology records that farmers
727 grow crops on land they own or rent, neither the ontology, nor any software used to build or
728 manipulate it, knows anything about what a farmer, a crop or land is, or what owning and renting
729 mean, beyond what is explicitly encoded in the terminology used: the same information could be
730 encoded using the labels: X, Y and Z for farmers, crops and land – the use of meaningful terms is
731 simply an aid to interpretation. If we place model entities and relationships, and the real-world
732 entities and relationships they are intended to represent, into distinct but linked ontologies, it
733 may be easier to avoid any confusion between those observed and those in the model. It should
734 also help modellers to keep in mind that the ontologies themselves are just descriptive tools
735 which, inevitably, will leave out or distort many aspects of what they describe.

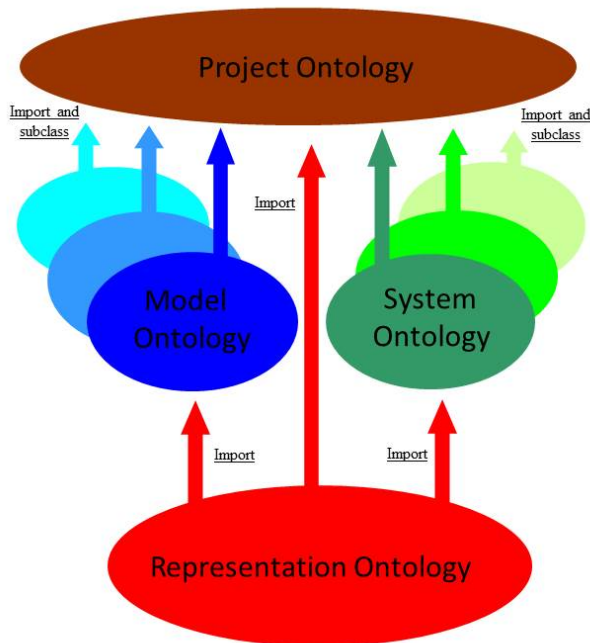


Figure 3: Ontologies for SES Modelling.

736 Figure 3 illustrates the set of ontologies that might be used in a modelling project, and
737 the relationships between them. Here there are four kinds of ontology: the project ontology,
738 the system ontology (or ontologies), the model ontology (or ontologies) and the representation
739 ontology.

740 The most general is the **project ontology**, which combines the conceptual, primarily qual-
741 itative model of a domain of discourse, enquiry or research – such as SESs – with concepts
742 encoding the general approach taken to modelling the domain – such as ABM. It will include the
743 more abstract, high-level terms that are fundamental to conceptualizing the domain, including
744 both terms that apply to real-world items, and those which apply to items within models.

745 A **system ontology** would contain concepts, and individuals, intended to capture the enti-
746 ties, relationships and processes present in a specific part of the real world. Primarily, it would
747 encode the modellers’ conceptual model; if stakeholders’ conceptual models were incompatible
748 with this, the differences would be captured by notations describing these stakeholders’ *beliefs*
749 about the system. The additional ovals represent the fact that a modelling project may cover
750 multiple systems, situations or scenarios. A system ontology *imports* the project ontology –
751 meaning that the terms in the project ontology are available for use in defining terms in the
752 system ontology. The figure illustrates that there may be multiple system ontologies, one for
753 each system modelled within the project; but different system ontologies within a modelling
754 project may encode incompatible conceptual models. However, each must be compatible with
755 the project ontology, and the project ontology may thus require amendment when a new target
756 system is added to the project.

757 A **model ontology** is concerned with the entities in a specific model and their relationships.
758 A model ontology, like a system ontology, will import the project ontology. There may be several
759 within a modelling project, and even several corresponding to different models of the same system
760 – for example, models at different levels of detail, or attempting to capture the views of different
761 groups of stakeholders. Again, different model ontologies may not be compatible with each other,
762 so again, the project ontology may need amendment when a new model is added to the project.

763 The **representation ontology** encodes the relationships between the system and project
764 ontologies and the model ontology or ontologies. It imports all the other ontologies, and adds
765 only the links between items in the project and system ontologies, and the items that represent
766 them in one or more model ontologies.

767 A hypothetical example drawn from a real land use change modelling project, FEARLUS (Pol-
768 hill et al., 2001), and its enhancement to include a species metacommunity model as FEARLUS-
769 SPOMM (Polhill et al., 2013) is described in Appendix 1. A much more detailed account of
770 the use of ontologies in a large-scale research project involving ABM (alongside quantitative and
771 qualitative empirical methods) is available in Salt et al. (2016), although this does not employ
772 quite the same approach as proposed here.

773 5. Summary and Conclusions

774 We have argued that the social aspects of SES need to be modelled explicitly (section 1 and
775 section 2). Given this, however, modelling SESs raises particular problems because:

- 776 1. Additional kinds of complexity are involved when a system includes human agents – who
777 may attempt to change the structure and dynamics of the SES they are part of, in conflict,
778 in competition or in cooperation with each other (section 2.1);
- 779 2. The terminology used in the assessment of SESs is ill-defined and contested. Important
780 concepts in the assessment of SESs, like “resilience”, “sustainability” and “health”, are

781 highly discipline-dependent, ambiguous, problematic, and contested (section 2.2). These
782 concepts cannot be measured directly, and a wide range of indicators have been used.

783 3. Closely connected to point 1, much SES modelling takes place in adversarial political
784 contexts, so that modelling decisions themselves become political (section 2.2).

785 4. Good data on social aspects of SESs are often unavailable (section 3.1), and although theory
786 can sometimes compensate for absent data, theories of human behaviour are scattered
787 across psychology and the social sciences, generally contested, and often lacking causal
788 mechanisms.

789 Considering these problems, and the range of possible modelling aims (section 3.2), we con-
790 clude that on its own, the nature of the modelled system does not determine the model or
791 models required, and advocate thinking in terms of modelling projects, which may involve one or
792 many simulation models, or even none at all (section 3.3). However, for at least those modelling
793 projects where explanation (deepening the understanding of the system or systems modelled) is
794 an important aim, we consider that among the range of possible approaches to modelling SESs,
795 which we briefly outline (section 3.4), the expressivity of agent-based models (ABMs) is necessary
796 to successful SES modelling, although ABMs may include elements of systems dynamics (SD)
797 and cellular automata (CA) modelling within them (section 4.1).

798 Along with their advantage in expressivity, and indeed as a consequence of it, ABMs do
799 have significant drawbacks: their numerous tunable parameters pose difficulties for validation
800 and their complex structure for transparency (section 4.2). We suggest a number of ways in
801 which the use of formal ontologies can ameliorate these problems (section 4.3) in the context of
802 modelling projects, covering the processes of design, implementation, stakeholder involvement,
803 and validation. We argue in particular that it is vital to make as clear as possible what each
804 model is for, what it includes and what it is known to leave out, and therefore recommend the
805 use of ontologies to encode relationships between the overall project, its models, and the systems
806 modelled.

807 It should be said that even ABMs have difficulty capturing cross-scale interactions between
808 local, regional, national, continental and global levels. SESs which would once have been rel-
809 atively self-contained are today increasingly affected, often adversely, by distant events, or by
810 the sum of events over large areas or the entire globe. Changes in the supply of or demand for
811 commodities in one country can lead to the destruction (or at least temporary preservation) of
812 forests in another; species accidentally or deliberately introduced, particularly but not exclu-
813 sively to isolated regions such as small islands, can devastate local ecosystems; and of course
814 anthropogenic climate change is affecting or will affect every SES on the planet. The need to
815 model such cross-scale networks of causal connections reinforces the need to think in terms of
816 modelling projects, using ABMs on different spatio-temporal and organizational scales, linked
817 through a project ontology.

818 Similarly, there has been little progress in modelling the kind of social complexity that people
819 inhabit daily and routinely, if by no means always easily. People frequently belong to or take part
820 in multiple social formations, both formal and informal: as members of a household, immediate
821 and extended family, friendship networks, social, professional, political and religious groups.
822 They act as employees or employers, tenants or landlords, buyers and sellers, students and
823 teachers, citizens – to name only a few broad classes of social role. As individuals, we somehow
824 handle these complexities; yet no model, ABM or otherwise, ever deals with more than a small
825 number of the groupings we belong to or the roles we adopt, let alone the complex interactions
826 between them. Progress in developing ABM representations of human agency, and in particular,
827 the way in which the decisions and actions of collectives such as households, firms and states

828 emerge out of those of the individuals belonging to them, is therefore essential if agent-based
829 modelling is to fulfill the potential we believe it has.

830 The over-riding message of this paper is that SES modellers need to make use of agent-based
831 modelling approaches, and to work on extending the capabilities of these approaches to deal with
832 types of complexity beyond their current scope. We recommend the use of formal ontologies as a
833 means to maintain and improve transparency as both individual models and modelling projects
834 grow in complexity. But above all, whether they choose to follow this recommendation or not,
835 they need to make as clear and explicit as they can, to themselves and others – fellow-researchers,
836 policy-makers, stakeholders, and concerned citizens – the aims, the claims, the context, and the
837 limitations of their models. This is both a scientific and a social obligation for all modellers; but
838 the special features of SES modelling (both scientific and political), and the challenges sketched
839 in the preceding paragraphs, make it particularly necessary in that domain.

840 Acknowledgements

841 J. Gareth Polhill receives funding from the Scottish Government’s Rural Affairs, Food and the
842 Environment Strategic Research Programme 2016-2021. The work by George A.K. van Voorn and
843 Gert Jan Hofstede was funded by the Wageningen University and Research Resilience investment
844 theme.

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1236 Appendix 1

1237 To illustrate the potential advantages of the multi-ontology approach in ABM projects, we take
1238 as an example the “FEARLUS-SPOMM” model (Polhill et al., 2013), which was designed and
1239 implemented as part of the long-running FEARLUS (Framework for Evaluation and Assessment
1240 of Regional Land Use Scenarios) project, first described in Polhill et al. (2001). Several versions
1241 of the FEARLUS model were developed, the latest being FEARLUS-SPOMM, which coupled a
1242 species metacommunity model, SPOMM (Stochastic Patch Occupancy Metacommunity Model),
1243 which is an enhanced version of SPOMSIM (Moilanen, 2004), to the FEARLUS core. The
1244 purpose of FEARLUS-SPOMM was to examine the consequences of different possible government
1245 incentive schemes aimed at preserving and increasing biodiversity on farmers’ lands. By the time
1246 FEARLUS-SPOMM was implemented, a prototype feature had been added to FEARLUS (Polhill
1247 et al., 2008) to produce what is called here a model ontology, and a partial project ontology,
1248 and Polhill et al. (2013) includes a model ontology encoded as a UML diagram, but FEARLUS-
1249 SPOMM was designed and implemented without use of a separate system ontology. We aim
1250 to show here that, even devised in retrospect, such an ontology can significantly improve ABM
1251 transparency.

1252 Figure 4 shows an adapted version of the FEARLUS-SPOMM model ontology, at lower left,
1253 along with versions of a FEARLUS project ontology (top), and a FEARLUS-SPOMM system
1254 ontology (lower right). The FEARLUS project ontology is a (partial) representation of the
1255 modellers’ conceptual model of the FEARLUS project domain – regional land use scenarios –
1256 prior to the work leading up to the coupling of FEARLUS and SPOMM. The FEARLUS-SPOMM
1257 model ontology is a (partial) representation of the addition to this conceptual model needed to
1258 include the species metacommunity model, and the types of government incentive schemes to be
1259 explored.

1260 Links between the three ontologies are shown by the thicker, dotted lines. There are four
1261 types of relation between concepts in the ontologies. Three of these occur both within the
1262 three labelled ontologies, and linking nodes in different ontologies: “subclass-of”, “part-of”, and
1263 “relates-to”. The node at the tail of a “subclass-of” link names a subclass, or subconcept, of
1264 the concept named by the node at the head of the link. Instances of the concept named at
1265 the tail of a “part-of” link are, or can be, parts of instances of the concept named at its head.
1266 The “relates-to” link stands for any other type of relationship between instances of the concepts
1267 named at its head and tail; these links are labelled to identify the relationship (in the full version
1268 of the ontology, these relationships would themselves be formally defined). The fourth type of
1269 link, “represents”, runs between a node in the model ontology, and a node in either the system
1270 or project ontology, specifying that an instance of the model ontology concept at the link tail

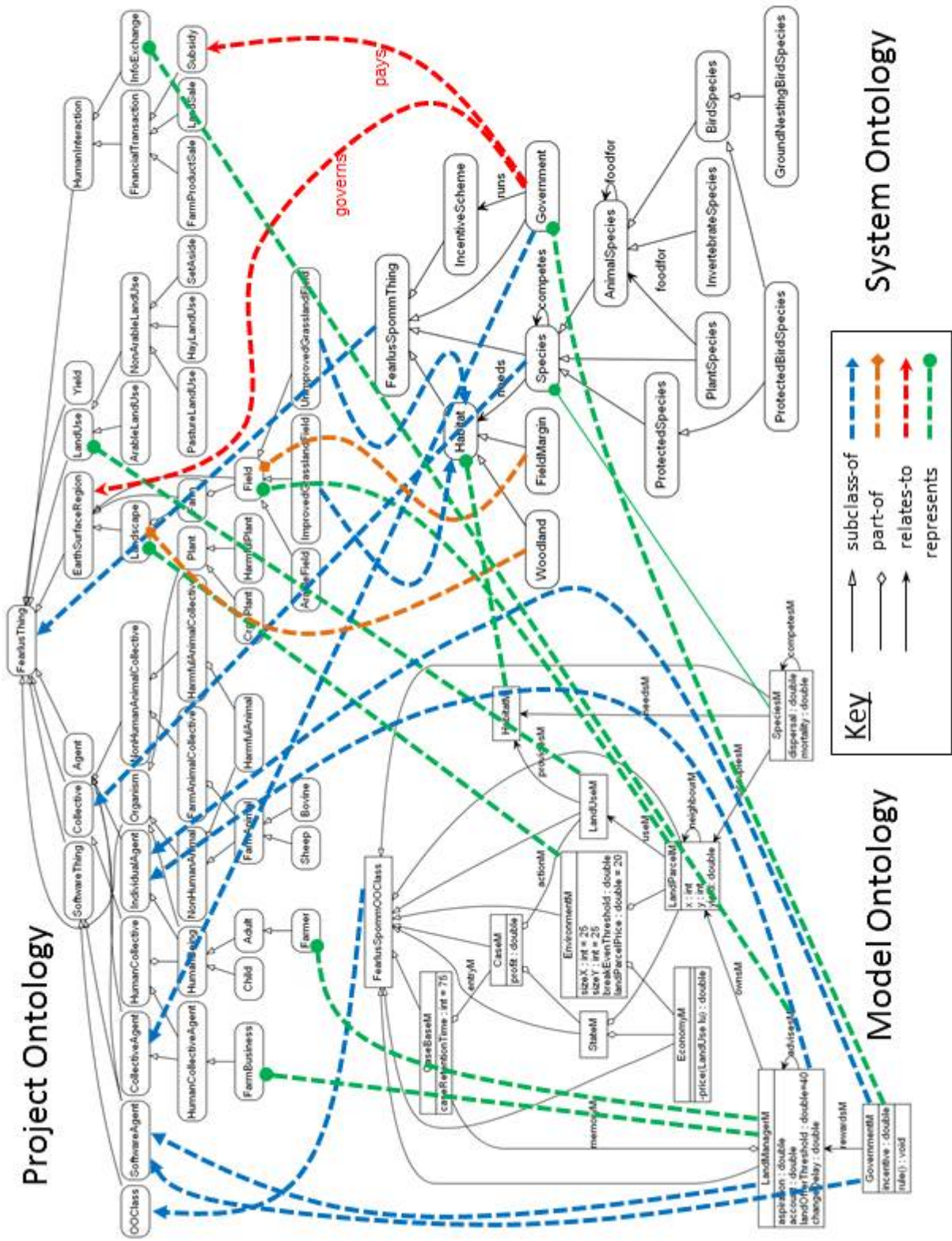


Figure 4: FEARLUS-SPOMM ontologies.

1271 is intended to represent an instance of the system or project ontology concept at the link head.
1272 We draw attention to the following points in the figure:

- 1273 • All three ontologies shown contain fewer nodes, links, and types of links than full ontologies
1274 would require. The representation ontology is not shown separately; it is visualized as the
1275 set of “represents” links. Within the project ontology, only “subclass-of” and “part-of”
1276 links are shown. A few “relates-to” links are shown in the model ontology and system
1277 ontology.
- 1278 • Names of nodes within the model ontology are given a final “M” as a reminder that they are
1279 pieces of software. All the nodes in this ontology stand for “classes” in the object-oriented
1280 language Objective C, in which FEARLUS-SPOMM is written. Just two of these nodes
1281 identify classes of SoftwareAgent: pieces of software that encode procedures for making
1282 decisions and assessing the results of those decisions as a program runs. (The distinction
1283 between “software agents” and other pieces of code depends on how they are viewed by
1284 the modeller as much as on their intrinsic properties.)
- 1285 • The two classes of SoftwareAgent within the model ontology (LandManagerM and Govern-
1286 mentM) also have “subclass-of” links to the node IndividualAgent in the project ontology.
1287 An “individual agent” contrasts with a “collective agent”: the decisions of the latter, but
1288 not the former, emerge out of the interactions of other agents that they (in some sense)
1289 comprise. Thus in reality, the decisions of a government – even in a dictatorship – arise as
1290 a result of interactions between multiple individuals, and indeed, smaller collective agents
1291 such as committees and departments – but the FEARLUS-SPOMM GovernmentM agent
1292 has no such internal structure. The situation with regard to the other class of IndividualA-
1293 gent within FEARLUS-SPOMM, the LandManagerM, is more complicated: it is unclear
1294 whether a LandManagerM represents a human individual (a farmer), or a farm *business*,
1295 which generally includes more than one person, and has a distinct legal existence (in the
1296 normal FEARLUS context of the UK). In the formal representation ontology, these links
1297 would be annotated with classificatory terms, themselves part of a hierarchy of types of
1298 representation, designed to elucidate both those features of the link head which the link
1299 tail captures, and those it does not.
- 1300 • Turning to parts of the physical world, a LandParcelM represents a Field (in the project
1301 ontology: fields are common to all systems modelled in the FEARLUS project). But
1302 features attached to LandParcelM show that its spatial position can be specified by a
1303 single pair of integer coordinates, indicating that the LandParcelMs form a grid, and are
1304 all of the same size. Real fields do not in general conform to this pattern, and have many
1305 other conceptually important features which FEARLUS’s LandParcelMs lack. Of course,
1306 even the project ontology cannot include all the features even of something as relatively
1307 simple as fields, but features and relationships can be added to those ontologies *as they*
1308 *become significant in ongoing work*, for example through being mentioned in a stakeholder
1309 or expert interview. They would then serve as a reminder of what a model leaves out, and
1310 a source of suggestions for enhancing it.
- 1311 • The EnvironmentM is shown as representing a project ontology Landscape, but in this case,
1312 the model ontology concept actually contains elements that do not correspond to anything
1313 in a real-world landscape, but to the prices of farm products. The project ontology as
1314 shown omits these; if constructed in advance, it would certainly have included them, but
1315 this illustrates another general point: a simulation model itself can suggest lacunae in
1316 the conceptual model encoded in a project or system ontology. Conversely, the fact that

1317 EnvironmentM has no straightforward counterpart in the project or system ontology at
1318 least casts some doubt on the way the simulation model is structured.

1319 • Other nodes in the model have no “represents” links at all. All except the top-level Fear-
1320 lusSpommThing node, which is a notational convenience, relate to the way in which a
1321 LandManagerM decides what LandUseM to apply to a LandParcelM. This feature of the
1322 model (encoded in the FEARLUS-SPOMM classes StateM, CaseM and CaseBaseM) is in-
1323 tended to implement a simplified version of “Case-Based Reasoning” (Aamodt and Plaza,
1324 1994), an artificial intelligence technique in turn claimed to capture features of human ex-
1325 pert decision-making; but how far the FEARLUS-SPOMM model is intended to represent
1326 how real farmers (or farm businesses – see above) choose land uses is not clear. CaseBaseM
1327 could be taken to represent either the personal memory of a Farmer, or the “institutional
1328 memory” of a FarmBusiness. It is worth noting that earlier versions of FEARLUS employed
1329 different decision-making methods, see for example Polhill et al. (2001).

1330 • The links between the system and project ontologies also point up interesting issues, in this
1331 case with regard to the integration of two conceptual models. The Government node in the
1332 system ontology has three links to nodes in the project ontology. One is a “subclass-of” link
1333 to the CollectiveAgent node, the others are “relates-to” links noting that a Government
1334 governs an EarthSurfaceRegion (the project ontology does not include more specific nodes
1335 for polities, this might suggest adding at least one such node, but the model ontology does
1336 not appear to need to include this concept), and that a Government pays Subsidy (again,
1337 this might suggest the need for additional nodes and in this case, more information about
1338 how the model represents this fact seems desirable).

1339 • The other system-project links concern the system concepts Species and Habitat. Species
1340 is linked to the project node Collective as a subclass, but this raises the question of what
1341 “species” means in the context of a species metacommunity model. The individual members
1342 of a species are not in fact represented, only the presence or absence of some members of
1343 the species in specific areas, and their ability to persist there, and spread to neighbouring
1344 areas, so the species is treated more like an amorphous mass than a collective – which is, in
1345 the context of this type of conceptual model, quite valid. But this suggests that the concept
1346 does not fit easily into the conceptual model underlying FEARLUS, so modellers should
1347 beware of problems arising from this imperfect fit. Similarly, “subclass-of” links going
1348 the other way, from the project to the system ontology, link UnimprovedGrasslandField
1349 and ImprovedGrasslandField to Habitat. That seems unexceptionable – unimproved and
1350 improved grassland fields are both surely types of habitat. But should there also be a
1351 subclass-of link from Field to Habitat? Or perhaps habitats should not be encoded in
1352 nodes at all, but in links: a given type of field being a “habitat-for” a particular range of
1353 species.

1354 The foregoing examples demonstrate how the use of ontologies can bring to the surface deep issues
1355 that arise in modelling, concerning the relationships between conceptual and software models, and
1356 between conceptual models themselves. Such issues arise particularly when comparing models
1357 (Cioffi-Revilla and Gotts, 2003), when extending the domain of a modelling project (as in the case
1358 of FEARLUS-SPOMM), and when combining existing software or conceptual models (again, as
1359 in the FEARLUS-SPOMM case). Of course, we do not claim such tasks are impossible without
1360 the use of ontologies, but that, particularly with a modelling approach as expressive as ABM,
1361 they have great potential to assist in model development, assessment, comparison, extension and
1362 combination.