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1 **A participatory Bayesian Belief Network approach to explore ambiguity among**  
2 **stakeholders about socio-ecological systems**

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10 **Highlights**

- 11 • A participatory Bayesian Belief network method is proposed to sort out ambiguities among  
12 different stakeholders' perspective about how their socio-ecological system works.
- 13 • A Bayesian Belief modeling approach based on participation of stakeholders all along, from  
14 framing the research question to scenario exploration
- 15 • The method, applied on a case study, explored the ambiguities between local stakeholders and  
16 a landscape ecology scientist about the ecological effect of a complex landscape on natural  
17 enemies' pest control ecosystem service.

18 **Abstract**

19 Participatory modelling must often deal with the challenge of ambiguity when diverse  
20 stakeholders do not share a common understanding of the problem and measures for its solution.  
21 In this paper, we propose a framework and a methodology to elicit ambiguities among different  
22 stakeholders by using a participatory Bayesian Belief Network (BBN) modelling approach. Our  
23 approach consists of four steps undertaken with stakeholders: (1) co-construction of a  
24 consensual conceptual model of their socio-ecological system, (2) translation of the model into  
25 a consensual Bayesian Net structure, (3) individual parametrization of conditional probabilities,  
26 and (4) elicitation of ambiguity through the use of scenarios. We tested this methodology on  
27 the ambiguity surrounding the effect of an ecological process on a potential innovation in  
28 biological control, and it proved useful in eliciting ambiguity. Further research could explore  
29 more conflictual or controversial ambiguities to test this methodology in other settings.

30 **Keywords:** Uncertainty; Subjectivity; Landscape ecology; Biological control

31 **Data availability**

32 Contact: N. Salliou at [nicolas.salliou@gmail.com](mailto:nicolas.salliou@gmail.com) or +33 645196748

33 Software required: Netica (v 5.18)

34

## 35 **1. Introduction**

36 Modelling with stakeholders is widely recognized for its ability to enhance stakeholder  
37 knowledge and understanding of a system as well as clarify the impacts of potential solutions  
38 to a problem (Voinov and Bousquet 2010). Stakeholder participation enhances the success of  
39 the process in which such stakeholders are involved because it favors improved decision-  
40 making processes and fewer conflicts (Voinov and Bousquet 2010) as well as faster impact  
41 (Couvet and Teyssède 2013). However, involving stakeholders comes with specific  
42 challenges. Indeed, involving multiple parties from diverse backgrounds means that a spectrum  
43 of opinions, frames and ways of making sense must be accommodated (Brugnach et al. 2008).  
44 Such endeavor is particularly challenging as different stakeholders have equally valid ways of  
45 framing a problem (Dewulf et al. 2005). Stakeholders having radically different representations  
46 of a system is recognized as being associated with action situations exposed to “wicked  
47 problems” (Rittel and Webber 1973). A wicked problem is a complex issue to which there is  
48 no straightforward and definitive solution. Several authors suggest that, in such situations,  
49 stakeholders should construct a common understanding (Brugnach et al. 2008, Etienne 2010).  
50 However, creating a common understanding is challenged by many different types of  
51 uncertainties that complicate this endeavor (Brugnach et al. 2008).

52 Uncertainty is a widely recognized concept that has been approached differently in many  
53 different scientific domains (e.g. Knight 1921, Shannon 1948, Crozier and Friedberg 1977). In  
54 socio-ecological settings, three different types of uncertainties have been identified: epistemic  
55 uncertainty, ontological uncertainty (Walker et al. 2003), and ambiguity (Brugnach et al. 2008).  
56 Epistemic uncertainty is the most traditional way to consider uncertainties, as it represents the  
57 imperfection of knowledge. As Walker et al. (2003) puts it, epistemic uncertainty may be  
58 reduced by more research and empirical efforts. Ontological uncertainty refers to the inherent  
59 variability or unpredictability of a phenomenon (Walker et al. 2003), and ambiguity relates to  
60 the plurality of different persons’ representations of a system. By representation, we mean a  
61 mental model of external reality that allows people to interact with the world (Jones et al. 2011).  
62 Ambiguity occurs in particular when stakeholders build different representations about their  
63 environment (Brugnach et al. 2008).

64 As regards to modelling uncertainties, the Bayesian Belief Network (BBN) approach is  
65 recognized as particularly appropriate (Aguilera et al. 2011, Ropero et al. 2016), including in  
66 the case of modelling with stakeholder participation (Voinov and Bousquet 2010). In the field  
67 of environment management, participatory BBN modelling is recognized for its capacity to (1)  
68 represent and integrate knowledge from diverse disciplines and spheres, (2) explicitly support  
69 the inclusion of stakeholders' representations, and (3) take into account epistemic and  
70 ontological uncertainties (Düspohl et al. 2012). However, without a few exceptions (Henriksen  
71 et al. 2012, Kelly et al. 2013), BBN construction with stakeholders do not prescribe or guide on  
72 how to consider ambiguity as part of participatory modelling with stakeholders. Most of the  
73 time, different stakeholder's representations in participatory BBN are integrated either by  
74 averaging all representations in a single model (e.g. Shaw et al. 2016) or by choosing the "best  
75 available source of information" (Voinov and Bousquet 2010:1268, Holzkämper et al. 2012).  
76 Such simplification makes sense when the objective of a participatory BBN model is decision  
77 support (Cain et al. 2003) or prediction, because integrating all available information (scientific  
78 and non-scientific) in a single final model may improve the model's explanatory power. Such  
79 integration is not satisfactory when the modelling objective is not prediction but rather  
80 exploration of different framing issues and exchanges of representations among stakeholders to  
81 "illuminate core uncertainties" (Epstein 2008) like ambiguity. The objective of this paper is to  
82 present the testing of a participatory modelling method using BBN that enables the analysis,  
83 and comparison of the different representations brought forward by multiple stakeholders. This  
84 method allows for dealing with ontological uncertainty, which is common for BBN, in order to  
85 deal with ambiguity, which is less researched. A couple of papers mention this issue (Henriksen  
86 et al. 2012, Kelly et al. 2013), but do not provide an operational approach to deal with  
87 ambiguity, which is the purpose of the present paper and as such is an original proposition.

88

## 89 **2. Method**

### 90 2.1 Case study background

91 We tested our BBN participatory modelling approach in southwest France in an agricultural  
92 region specializing in fruit tree production (mainly apples) located on alluvial terraces along  
93 the Aveyron and Tarn rivers. Conventional apple orchards require intensive chemical  
94 treatments to control pests. Integrated pest management (IPM) in the 1980–90s promoted the  
95 use of natural enemies in the area to encourage fruit growers to implement biological control  
96 of some insect pests. Natural enemies are species which activity of predating or parasiting other  
97 species considered as pests may reduce their negative impacts on crops. Recent public policies

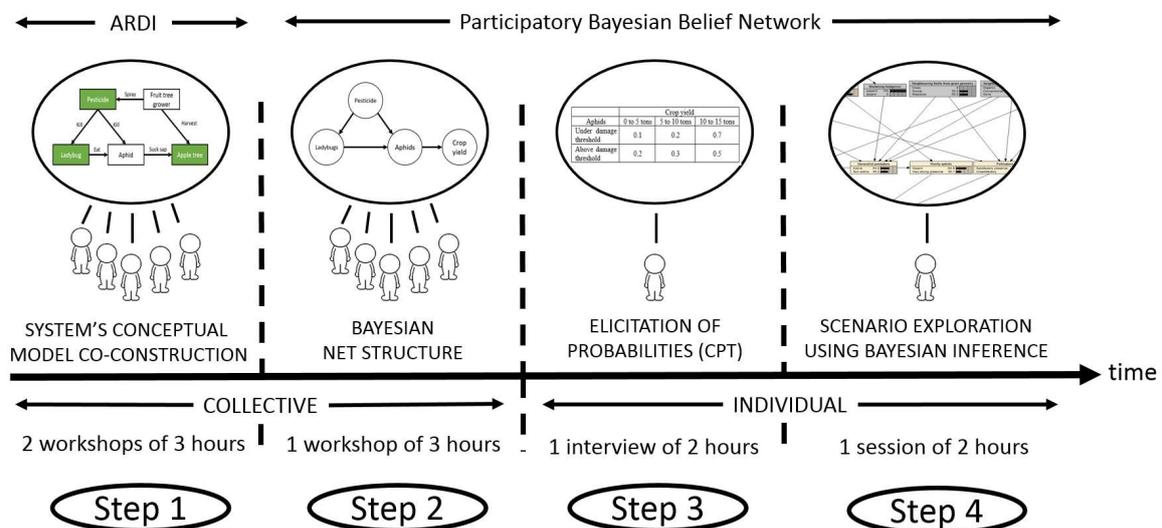
98 in France are trying to reduce farmers' pesticide use by 50% by 2025. They foresee the  
99 possibility of doing so by enhancing natural enemy activity by engineering pest-suppressing  
100 landscapes (Potier 2014). Some landscape ecologists' findings back up such potential  
101 innovation by demonstrating that a high presence of natural habitats such as meadows and  
102 woods enhances biological pest control by providing food and shelter for these natural enemies  
103 (Bianchi et al. 2006, Rusch et al. 2016). Some authors modelled pest-suppressing landscapes  
104 and indicated that agent-farmers would always benefit from such landscape-scale management  
105 (Cong et al. 2014). Another theoretical model indicated a high outcome when farmers cooperate  
106 in the management of natural enemy habitats (Bell et al. 2016). However, scant attention has  
107 been paid to the question of whether it is in the interest of farmers to manage habitats at the  
108 landscape scale (Cong et al. 2014). In this regard, we previously identified that, in this area,  
109 local stakeholders (whether farmers or their advisors) had representations of their landscape in  
110 which landscape stimulated occasional pest damage, and no effect whatsoever of the landscape  
111 on natural enemies was mentioned (Salliou and Barnaud 2017). This difference in  
112 representations between scientists and local stakeholders came as a surprise, as the effect of  
113 local or regional landscapes on the natural enemy populations of orchards is reported by many  
114 authors (see Simon et al.'s 2010 synthesis). A top-down science-based approach to innovation  
115 might consider scientific findings as more relevant than farmers' local knowledge. In our co-  
116 innovation approach however, we wanted to give careful consideration to both scientific and  
117 local representations, which are a priori equally legitimate in regard to this potential innovation  
118 (Jalonen 2012). The modelling approach presented here aims to explore ambiguity between  
119 landscape ecology findings and local stakeholders' knowledge about the effect of the landscape  
120 on natural enemies and pest control. In our study area, the modelling process involved five  
121 willing stakeholders: a conventional fruit tree grower, an organic fruit tree grower, a pedagogic  
122 fruit farm manager, a technical advisor, and a landscape ecology researcher. These participants  
123 are representative of the diversity of local stakeholders involved in the fruit tree production  
124 sector studied.

125

## 126 2.2 Modelling approach

127 We designed a four-step protocol in order to compare stakeholders' representations about the  
128 same socio-ecological system (Figure 1). We describe here the global modelling approach and  
129 main steps, which are detailed in later sections. As a first step, stakeholders (the scientist and  
130 local stakeholders) co-constructed a consensual conceptual model of the socio-ecological  
131 system using the ARDI methodology, specifically designed for it (Etienne et al. 2011). In a

132 second step, this conceptual model was collectively turned into a Bayesian net structure. This  
 133 Bayesian net structure is a collectively agreed understanding among involved stakeholders  
 134 about how main variables and states of the system are defined and connected. In the following  
 135 step, each stakeholder individually parametrized the Bayesian net structure by eliciting  
 136 probabilities attached to each variable in the system. Doing so, we finally constructed five  
 137 individual BBNs of the same socio-ecological system conceptualization, one for each  
 138 stakeholder. As a final step, we applied the same scenario of a pest-suppressing landscape to  
 139 each individual BBN. The impact of the scenario on each individual BBN model was then  
 140 discussed together with each participant. Ambiguities were analyzed by comparing the effect  
 141 of the same scenario on each stakeholder's BBN.

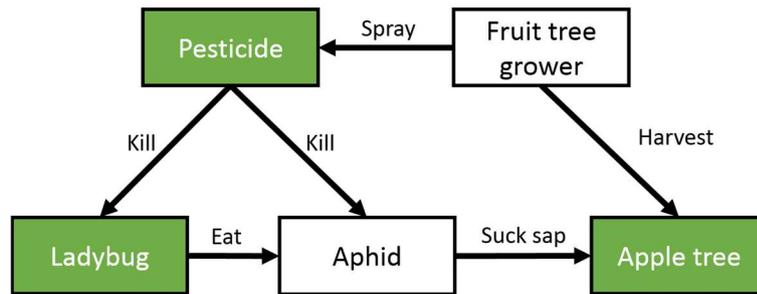


142  
 143 *Figure 1: The four main steps of our participatory BBN modelling process.*  
 144 *Note: ARDI: participatory methodology to co-construct a conceptual model of a socio-ecological system following*  
 145 *Actors (A), Resources (R), Dynamics (D), and Interactions (I) elicitation workshops. CPT: conditional probability*  
 146 *table.*

148 2.2.1 Co-constructing a consensual conceptual model of a socio-ecological system using the  
 149 ARDI methodology (step 1)

150 The ARDI (Actor–Resource–Dynamic–Interaction) method is specifically designed to build  
 151 together with stakeholders a consensual conceptual model of a socio-ecological system (Etienne  
 152 et al. 2011). It consists of a series of workshops where stakeholders are aided by a facilitator to  
 153 build collectively a conceptual model of a socio-ecological system representing its key actors  
 154 (humans and non-humans), its key resources, their dynamics, and the interactions among them.  
 155 Workshops first focus on listing Actors (A) and Resources (R) and eventually Dynamics (D).

156 Finally, the last step is about synthesizing and connecting previously identified actors,  
157 resources, and dynamics to form the final Interaction (I) diagram. This interaction diagram is  
158 the final conceptual model of the socio-ecological system. The interaction diagram consists of  
159 boxes for actors and for resources, as well as arrows connecting them when a causal interaction  
160 is mentioned between some of these boxes. Each arrow is topped with an action description  
161 characterizing the nature of the interaction (Figure 2).



163  
164 *Figure 2: Example of a simplified interaction diagram using the ARDI methodology.*  
165 *Note: Green boxes indicate resources and black boxes indicate actors in the system.*

166  
167 The construction of such diagrams enables a consensual conceptualization of the socio-  
168 ecological system among stakeholders involved in the modelling process. In order to achieve  
169 this objective, several principles are followed during the workshops:

- 170 • Each stakeholder is invited to indicate the resources, actors, processes, and interactions  
171 that are important to him regarding the socio-ecological system at stake. The method is  
172 neutral regarding stakeholders' proposals, as every proposal is considered legitimate.
- 173 • Each proposal made by a stakeholder should be explained to the other stakeholders,  
174 discussed, and agreed upon.
- 175 • The facilitator eases the agreement process by eventually reframing each stakeholder's  
176 proposal with his agreement.

177 This method is particularly interesting because it facilitates the step-by-step construction of a  
178 consensual conceptual model by stakeholders. The final conceptual model is consequently well  
179 understood and appropriated. Ensuring this common structure of understanding is critical for  
180 further individual comparison of each stakeholder representation of this system in the last step  
181 of our modelling approach.

182

183 2.2.1.1 The consensual representation in our case study

184 The ARDI conceptual model of our studied system was constructed with the five participants  
185 in response to the following question: “What coordinated actions might be undertaken for  
186 biological control of insect pests?” The model was developed during two workshops of three  
187 hours each (Figure 1). The first workshop focused on listing Actors (A) and Resources (R). The  
188 second focused on the creation of the Interaction (I) diagram. No key Dynamic (D) (whether  
189 social or ecological) was judged relevant to be detailed even though the possibility was open to  
190 participants. The final interaction diagram is presented in the Annex.

191

## 192 2.2.2 Participatory Bayesian Belief Network

### 193 2.2.2.1 General principles of Bayesian Belief Network modelling

194 A Bayesian Belief Network is a multivariate model for a set of variables, defined by three main  
195 components:

- 196 1. A **directed acyclic graph** (DAG) which connects variables together when they are  
197 statistically dependent. Figure 3 is an example of a DAG involving four variables  
198 visualized as nodes indicating the variable’s name.

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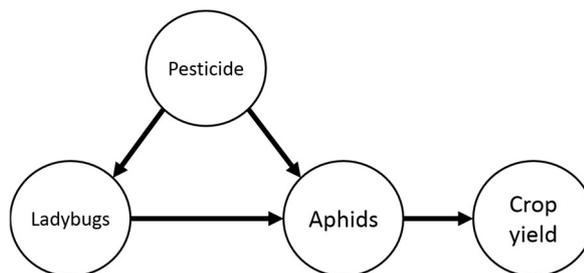
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*Figure 3: Example of directed acyclic graph (DAG) with nodes indicating variables.*

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Arrows between nodes indicate causal relationship and are visualized as directed links that point from cause to effect. For example here, aphids are dependent on pesticide use, which aims at killing them, and ladybugs, which prey on them.

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2. Each variable is defined by several **states**. For example, the aphid variable may have two states: “under damage threshold” and “above damage threshold”. In pest control, “damage threshold” refers to a level of pest population above which significant damages are predicted. These states must represent the full scope of possible states for this variable in the network considered.
3. Each variable has a **conditional probability table** (CPT), indicating all conditional probabilities between connected variables. For example, if we consider that the variable, crop yield, has three states “0 to 5 tons”, “5 to 10 tons”, and “10 to 15 tons”, the CPT for the crop yield variable might be as in Table 1:

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Aphids		Crop yield		
		0 to 5 tons	5 to 10 tons	10 to 15 tons
Under damage threshold		0.1	0.2	0.7
Above damage threshold		0.2	0.3	0.5

*Table 1: Conditional probability table for the crop yield variable*

Table 1 indicates, for example, that under the condition that aphids are under damage threshold the probability of the crop yield variable being between 5 and 10 tons is 0.2, i.e. 20%.

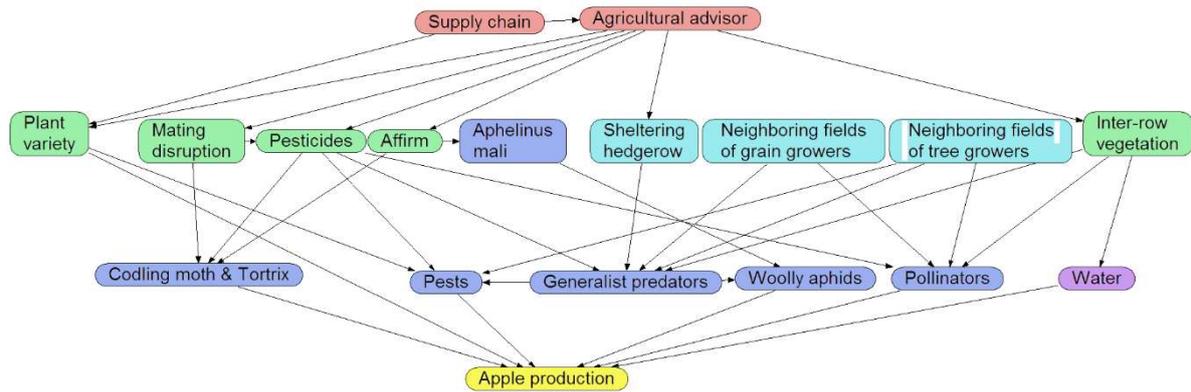
With these three components, the probability distribution of all the variables in the network can be calculated using Bayes' theorem. Once such Bayesian network has been set-up, it is possible to feed new information into the network about the probability distributions of one or several variables. This process is called Bayesian inference. In our example, it is possible that we actually know with certainty thanks to an observation that the Aphid variable is in the "Under damage threshold" state (probability of 1 for this state for the Aphid variable). As a consequence of this new piece of information, the Bayesian network can be updated regarding all the other probability distributions of the network's variables in order to accommodate this new piece of information. In our simple example, it means that the crop yield variable would take the distribution in the table line corresponding to "under damage threshold". This adaptation to new information is called "belief propagation". It is possible to use this belief propagation feature of BBN to explore scenarios with stakeholders (Düspohl et al. 2012). In this case, the new information input (i.e. "Aphids are under the threshold damage") is the scenario and the modification of the BBN by "belief propagation" is the effect of the scenario.

#### 2.2.2.2 From a consensual ARDI representation to a consensual Bayesian net structure (step 2)

The conceptual model was used as a baseline to be translated into a Bayesian net structure. By Bayesian net structure, we understand adding the DAG with characterization of all states. In this workshop, stakeholders had first to agree on variables and causality links to be kept from ARDI in the Bayesian net structure. Because both ARDI and Bayesian nets are causal networks, variables and arrows representing causal interactions could be transferred directly.

However, two main challenges may appear during this step. First, ARDI representation allows feedback loops and is consequently potentially a cyclic graph, in contrast to Bayesian networks, which are based on an acyclic graph approach. BBNs are known to create difficulty for the

252 integration of feedback loops (Düspohl et al. 2012, Landuyt et al. 2013). If feedback loops had  
253 been present, it would have been necessary to establish a Dynamic Bayesian Network approach,  
254 which can represent feedback loops (Grzegorzcyk and Husmeier 2009). This situation did not  
255 occur in our case study. The second challenge relates to the preparation for step 3, which deals  
256 with conditional probability elicitation. As the number of combinations of variable states grows  
257 exponentially with model complexity, probability elicitation quickly becomes impractical for  
258 the direct elicitation of probabilities by stakeholders (Shaw et al. 2016). Consequently, for direct  
259 elicitation of conditional probabilities to be manageable, we took action to keep the Bayesian  
260 net structure within a manageable complexity range. We proposed simplifications during the  
261 workshop to reduce proactively the quantity of variables and consequently limit the probability  
262 elicitation challenge in step 3. This simplification process has been recognized as good practice  
263 in participatory BBN when, after a broad range of potentially relevant variables have been  
264 defined, variables should be reviewed with regard to their relevance (Düspohl et al. 2012). Two  
265 types of simplification were considered: grouping similar variables and deleting irrelevant ones.  
266 We proposed grouping variables when similar behaviors were described. We proposed deleting  
267 variables when their relevance was not obvious. We proposed that every simplification  
268 identified should be submitted for approval by participants. If the participants did not reach  
269 consensus on a given simplification, the network was left untouched. We invited the  
270 participants to propose their own simplification proposals. Finally, we proposed adding some  
271 variables to the Bayesian net structure as we had good reason to think that some obvious nodes  
272 were forgotten or implicit. For example, from our previous round of interviews, agricultural  
273 advisors were regularly spontaneously mentioned as key agents by farmers regarding their pest  
274 management strategy (Salliou and Barnaud 2017). As they did not appear in the Bayesian net,  
275 they were proposed and agreed by stakeholders as a new variable. Stakeholders also made their  
276 own additions. They added for example the “mating disruption” technique variable. Mating  
277 disruption is a technique that releases mating pheromones to disrupt Codling moth and Tortrix  
278 reproduction. This whole translation process simplified the original ARDI representation,  
279 which included 38 nodes and 57 edges, into an 18 nodes and 27 edges Bayesian net structure  
280 (Figure 4).



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Figure 4: Final directed acyclic graph (DAG) constructed together with stakeholders.

Note: Colors distinguish variables about landscape (light blue), agricultural practices (green), social factors (red), insect populations (dark blue), abiotic factor (purple), and economic output (yellow).

Once the DAG structure was defined, the second step towards a final consensual Bayesian net structure was to define and agree on all variable states (Table 2). Participants agreed on most states relatively easily. Some involved much discussion, like the “rusticity” state of the Plant variety variable. This qualitative state hides divergent interpretations, from pest resistance to traditional tree varieties. This “rusticity” state was nevertheless kept in the final BBN structure as it is a term widely used by sellers and buyers of fruit trees. If this variable had been important for our final analysis, it might have been necessary to detail it. In general, we tried to avoid such polysemy to ensure a mutual understanding among participants.

Variable	States	Remark
Supply chain	Short, Long	n/a
Agricultural advisor	Coop and public, Pesticide seller, None	n/a
Plant variety	Rustic, Non rustic	Polysemy of “rustic”
Mating disruption	None, Present	n/a
Pesticides	Specific, Broad spectrum	Does not include, Affirm
Affirm	Used, Not used	Pesticide sprayed against Codling moth and Tortrix’s eggs
Aphelinus mali	Absent, Present	Natural enemy parasitizing woolly aphids
Sheltering hedgerow	Absent, Present	Aims to shelter natural enemies
Neighboring fields grain growers	Crops, Woods, Meadows	n/a
Neighboring fields fruit tree growers	Organic, Conventional, None	n/a
Inter-row vegetation	Mowed, Not mowed	Not mowing is thought to generate habitats for insects
Codling moth and Oriental fruit moth	Below 0.5% threshold, Above 0.5% threshold	Threshold = 0.5% of fruits observed in the orchard attacked by the pest
Pests	Harmful to sales, Not harmful	Except Codling moth and Tortrix and Woolly aphids

Generalist predators	Active, Non active	This variable covers many species of natural enemies. The state “active” is defined by stakeholders as a judgment based on quantity, diversity, and seasonality of these predators
Woolly aphids	Absent, Very strong presence	n/a
Pollinators	Satisfactory presence, Unsatisfactory	n/a
Water	Deficit, No deficit	n/a
Apple production	Fresh, For processing, Discarded	“Fresh” is the better priced type of apple on the market (no defect)

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*Table 2: Overview of BBN variables and states collectively discussed and agreed by participants*

298 2.2.3 Individual elicitation of each participant’s CPT and validation (step 3)

299 For each variable, the participants were asked to elicit a conditional probability table (CPT);  
300 this can be very time-consuming when model complexity is rising. If the direct probability  
301 elicitation workload is too heavy, an algorithm can be used to populate the CPT to ease the  
302 knowledge acquisition process (Das 2004). In our case, with 266 probabilities to be elicited, it  
303 meant that one probability had to be elicited every 40 seconds on average for a three-hour-long  
304 interview. We considered this process to be feasible without using an algorithm.

305 Another challenge in probability elicitation by stakeholders is that potentially not all  
306 participants are at ease with probability reasoning. In this regard, it has been demonstrated that  
307 elicitation using frequencies is more intuitive (Anderson 1998). Furthermore, it has been  
308 demonstrated that imagery is more effective than abstract presentations in mobilizing an  
309 expert’s experience (Brunner et al. 1987, cited in Anderson 1998). Consequently, during the  
310 interview, while asking questions to elicit probabilities, we showed images on cards about  
311 variables and states to facilitate the cognitive process.

312

313 Once the Bayesian net structure and individual CPTs were obtained, we compiled this  
314 information using the BBN modelling software Netica (V5.18). Through this process, we  
315 obtained five BBNs, one for each participant, representing their individual representation about  
316 the question of coordination for biological control. Each BBN was introduced to its “owner”  
317 and was validated individually. For some, minor corrections were made on the conditional  
318 probabilities previously indicated. However, in general, the participants recognized and  
319 validated their personal perspective.

320

321 2.2.4 Scenario exploration using Bayesian inference (step 4)

322 In this section, we introduce our original framework for ambiguity analysis using participatory  
323 BBN modelling. In the first section, we introduce our typology of uncertainties, detailing how  
324 ontological uncertainty and ambiguity are represented and understood in our participatory  
325 BBN. In the second section, we present the use of scenarios in BBN in order to shed light on  
326 ambiguities among stakeholders.

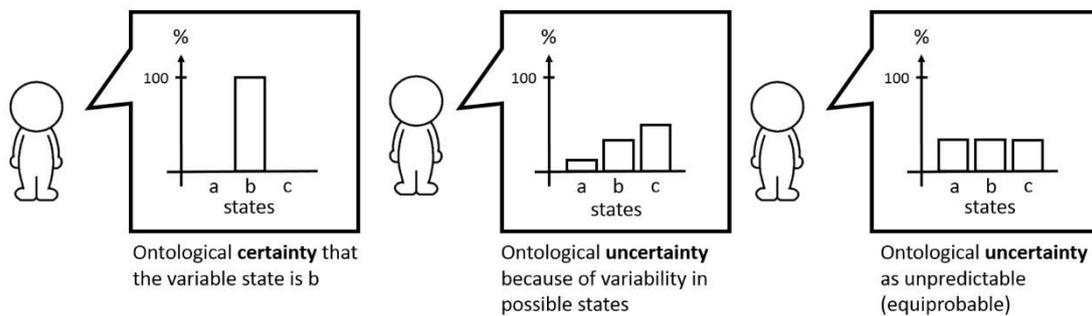
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328 2.2.4.1 Uncertainty typology

329 • Ontological uncertainty

330 Ontological uncertainty relates to inherent variability and unpredictability (Walker et al. 2003).  
331 When we analyze an individual BBN, we considered that ontological variability could be  
332 approximated through the probability distribution of a variable (Figure 5). To represent  
333 unpredictability of a variable, we follow the principle of indifference (a classical approach to  
334 assign probabilities in cases of ignorance (Castell 1998)). Following this principle,  
335 unpredictability situations were indicated by a normal distribution law or equiprobability.

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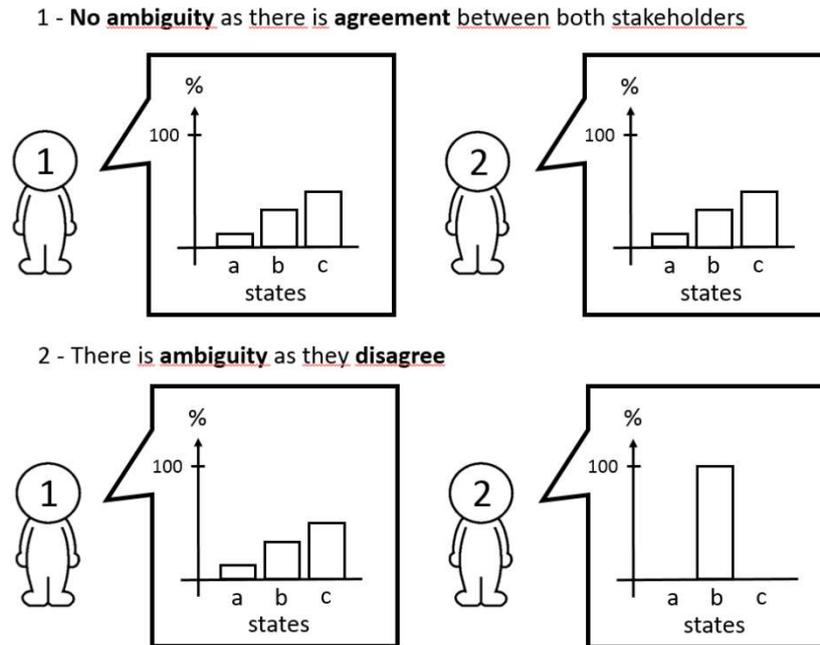


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338 *Figure 5: Typology of ontological uncertainties that can be analyzed in an individual Bayesian Belief Network*

339 • Ambiguity

340 Ambiguity occurs when stakeholders perceive their environment differently and build different  
341 representations about it (Brugnach et al. 2008). Representations are mental constructions  
342 elaborated by individuals in a certain context and period of time (Gaonac'h et al. 2006).  
343 Ambiguity can be analyzed by comparing individual BBNs – more specifically, by comparing  
344 probability distributions of the same variable among different stakeholders (see Figure 6).  
345 When two stakeholders share the same representation in a variable's probability distribution,  
346 there is no ambiguity.



348 *Figure 6: Agreement and disagreement between two stakeholders regarding ambiguity about a variable.*

349

#### 350 2.2.4.2 BBN scenario exploration and uncertainty analysis

- 351 • *BBN scenario*

352 In the previous section, we proposed a way to characterize two types of uncertainty in static  
 353 BBNs, that is to say, the stakeholder's representation at the moment of the probability  
 354 elicitation. Thanks to Bayesian inference, it is possible to "feed" each network with new  
 355 information. In our case, we call such new information a scenario. A scenario is explored by  
 356 imposing new probability distributions on one or several variables in a Bayesian network. When  
 357 a new piece of information is introduced in a BBN, all other variables update their probability  
 358 distribution accordingly. Changes in probability distributions on child nodes indicate the impact  
 359 of each scenario (Düspohl et al. 2012).

360

361 In this study, we tested the effect of a pest-suppressing landscape scenario, i.e. the scenario of  
 362 a complex landscape that would be favorable to natural enemies. According to the scientific  
 363 literature (Bianchi et al. 2006), landscape complexity means a high proportion of meadows,  
 364 hedgerows, and woods in the landscape (sometimes called semi-natural habitats). To explore  
 365 the effects of such landscape, we directly modified landscape variables in each individual BBN  
 366 (variables in light blue in Figure 4) to be as close as possible to these pest-suppressing  
 367 conditions. The variables explicitly referring to landscape variables in the BBN are the  
 368 following: (1) grain growers' neighboring fields with forest, meadow, and cereal crops as

369 potential states; (2) fruit growers' neighboring fields with organic, conventional, or absent  
 370 states; and (3) sheltering hedgerows with absence and presence as alternative states. As the  
 371 scientific literature says that complex landscapes that enhance biological control are composed  
 372 of a high proportion of semi-natural habitats (Bianchi et al. 2006), we imposed the following  
 373 information on each individual BBN:

- 374 1. Certainty of sheltering hedgerows presence (probability of presence: 100%)
- 375 2. Grain growers' neighboring fields are composed of woods and meadows with equal  
 376 probability (50%). It means also that there is certainty that there are no crop fields  
 377 (probability: 0%)
- 378 3. Fruit growers' neighboring fields are considered to be not present with certainty; there  
 379 is no orchards in the landscape (probability of "none" state: 100%)

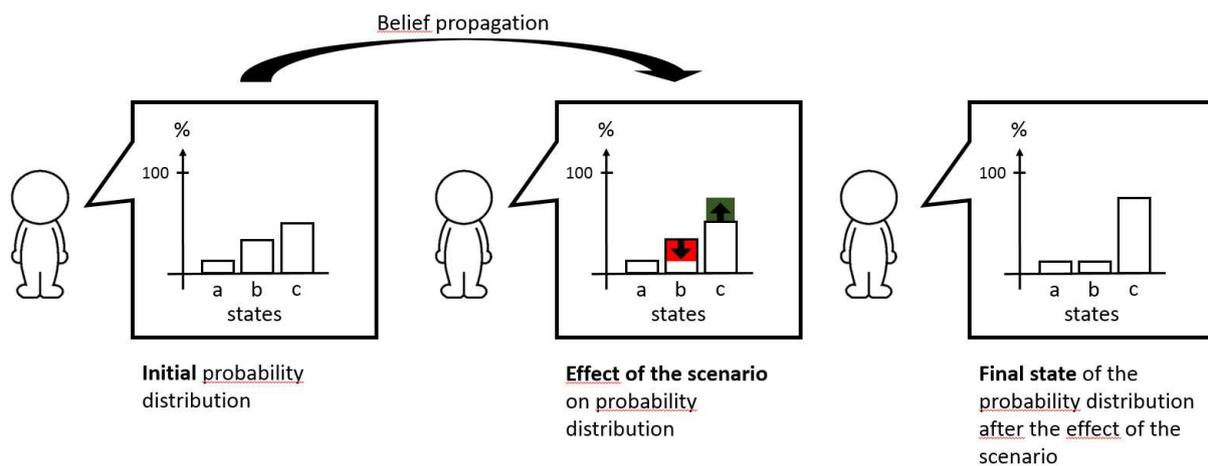
380

- 381 • BBN scenario and ambiguity analysis

382 When a scenario is tested, probability distributions may change, and two components of this  
 383 change can be analyzed for each stakeholder's BBN (Figure 7):

- 384 1. The effect of the scenario on probability distributions of variables through belief  
 385 propagation
- 386 2. The final state of probability distributions of variables once the BBN has been modified  
 387 by the scenario.

388



389

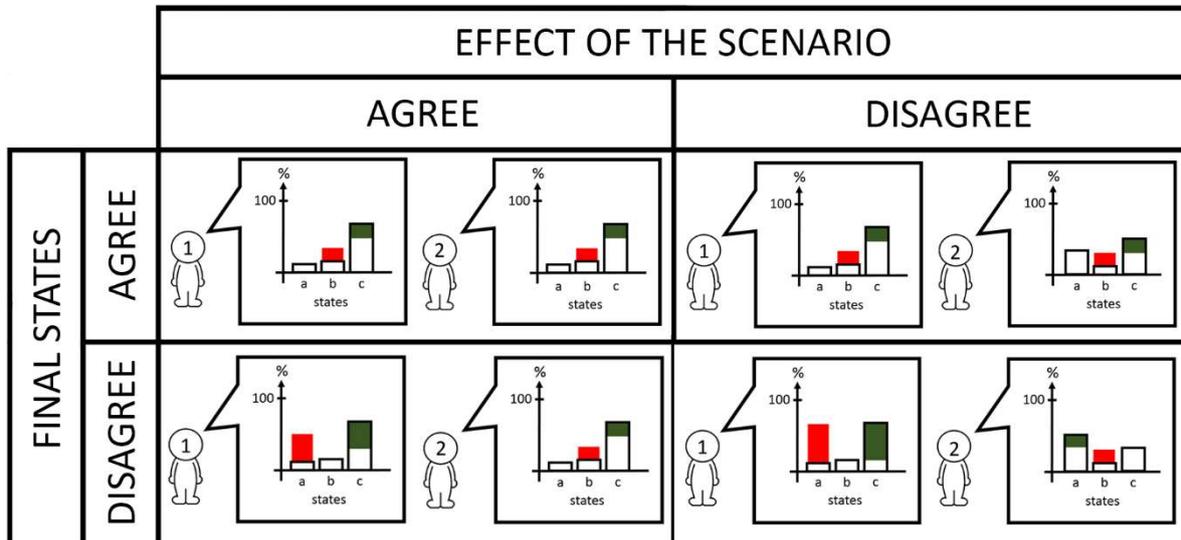
390 *Figure 7: Effect of the scenario on probability distribution through belief propagation. Distinction between the*  
 391 *effect of the scenario and the final state of a BBN variable.*

392

*Note: Red and green bars show the modification of the initial probability distribution.*

393

394 As a consequence, it is possible to analyze ambiguity on both effect of the scenario and final  
 395 states. As stakeholders may agree or disagree on both components, there are four potential  
 396 situations. They are represented in the Figure 8.  
 397



398  
 399 *Figure 8: The four standard cases covering agreement and disagreement about the effect of the scenario and the*  
 400 *final state of a variable from the BBN.*

401 *Note: Red and green bars show the modification of the initial probability distribution due to the effect of the*  
 402 *scenario. The bar surrounded by a black line is the final state for each state of the variable.*

403  
 404 Depending on the objective of the modelling process, scenario impact analysis may focus on  
 405 the effect of the scenario, final states, or both. In our case study, as we focused on the effect of  
 406 a complex landscape for different stakeholders, it is especially the effect of the scenario that we  
 407 analyzed.

- 408  
 409
  - BBN scenario and stakeholders' feedback

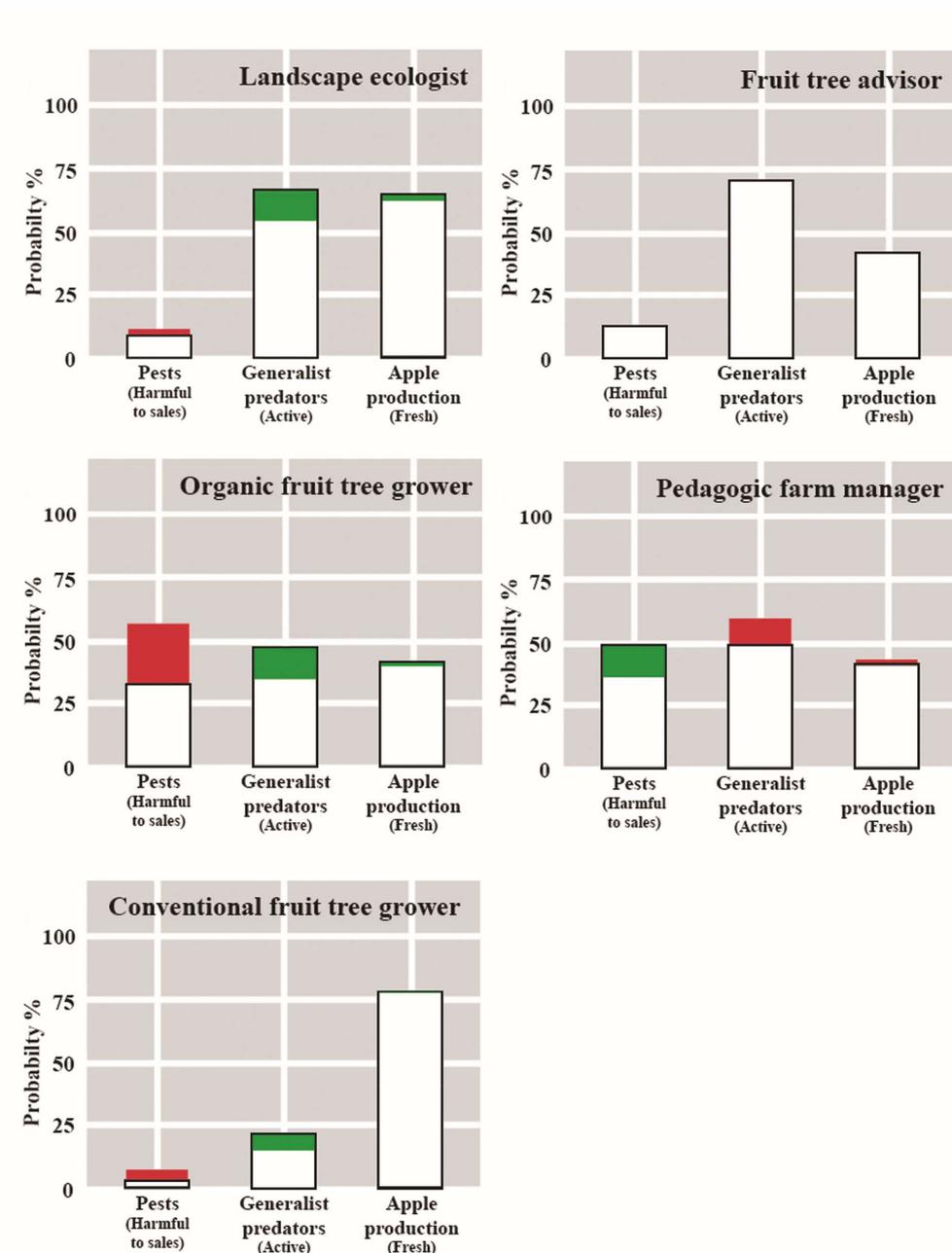
410 We explored together with each participant the effect of this scenario. Probably because they  
 411 participated in the construction of their BBN model, none of them mentioned any problem  
 412 understanding the model and the way the scenario impacted other variables. Participatory  
 413 exploration of the scenario allows for direct feedback from each stakeholder. Each stakeholder  
 414 indicated his interpretation of the effect of the scenario in his own words. Such feedback is  
 415 complementary to our formal analysis of uncertainty, which is conducted in the lab. Both  
 416 uncertainty analysis and stakeholders' feedback are used to shed light on each stakeholder's  
 417 representation of the socio-ecological system.

418

419 **3. Results**

420 Through the abovementioned modelling process, we constructed a conceptual model of the  
 421 socio-ecological systems agreed among the five participants, and then five individual BBNs  
 422 corresponding to each participant’s personal probabilities applied to this common socio-  
 423 ecological system structure. Once each BBN had been fed with the scenario about landscape  
 424 complexity, we analyzed and compared the effect of the scenario. The effect of the scenario on  
 425 all individual BBNs is presented in the graph in Figure 9.

426



427

428 *Figure 9: Effect of the “complex landscape” scenario on each stakeholder’s Bayesian Belief Network on the*

429 *Pests, Generalist predators, and Apple production variables in the BBN.*

430 *Note: Each bar corresponds to one state of the variable and is indicated within brackets. Red and green bars show*  
431 *the modification of the initial probability distribution due to the effect of the scenario. Bars surrounded by a black*  
432 *line are the probability value of the final state of each described variable. The “complex landscape” scenario is*  
433 *based on the following parametrization: Probability of “presence” of a sheltering hedgerow: 100%, Probability*  
434 *of “woods” and “meadows” as grain growers’ neighboring fields: 50%, probability of no orchards in neighboring*  
435 *fields: 100%.*

436

437 The effect of the scenario is diverse among participants regarding the Pests variable, ranging  
438 from -24.4% to +11.8%. Whereas the fruit tree advisor considers that such scenario has no  
439 effect whatsoever, other stakeholders’ models indicate a modification in the probability law of  
440 this variable. Three participants’ BBNs indicate a reduction in the probability that pests are  
441 harmful to sales. Whereas the landscape ecologist and conventional fruit tree grower are close  
442 to full agreement on the effect of the landscape on pests (-2% and -3.84% respectively), the  
443 organic fruit tree grower’s model indicates a reduction in this probability by 24.4%. This  
444 disagreement on the effect of the scenario relates specifically to the organic fruit tree grower’s  
445 belief that neighboring conventional orchards strongly favor pests. The pedagogic farm  
446 manager indicated a positive effect on pests harmful to sales (+11.8%). It is important to notice  
447 here that the pedagogic farm manager result should be considered with much care. Indeed, he  
448 indicated when giving information to fill his CPT that he did not know the effect of the  
449 surrounding landscape in the sense that, according to him, it might have a strongly positive or  
450 a strongly negative effect. Consequently, he indicated that he was unable to capture this  
451 variability through a probability law and considered the effect between landscape and pests to  
452 be unpredictable.

453

454 The effect of the scenario about the activity of generalist predators also varies among  
455 participants, ranging from -23.4% to +10.8%. Again, whereas the fruit tree advisor considers  
456 that such scenario has no effect whatsoever, other stakeholders’ models indicate a modification  
457 in the probability law for this variable. The same three stakeholders whose models indicated a  
458 reduction in pests as a result of the scenario connect a more complex landscape with more active  
459 generalist predators. The landscape ecologist and the organic fruit tree grower agree on the  
460 effect of a complex landscape on the activity of generalist predators (+10.8% and +10.7%  
461 respectively). The conventional fruit tree grower’s model indicates a close representation of  
462 this effect, with a +6.6% rise in probability of generalist predators being active. The pedagogic  
463 farm manager’s result, indicating a negative effect on generalist predators (-23.4%), should be  
464 taken with the same care due to the same unpredictability issue previously described.

465

466 The effect of the scenario on the probability law for the Apple production variable is consistent  
467 among all stakeholders. The effect of the scenario ranges from -3.2% to +2% probability of  
468 getting first quality apples (fresh). Apart from the fruit tree advisor, all indicated an effect of  
469 the scenario on this variable. This effect, however, appears very limited, as some stakeholders  
470 indicated when interviewed about it. Again, the same three stakeholders (landscape ecologist,  
471 organic fruit tree grower, and conventional fruit tree grower) shared a similar representation  
472 that a complex landscape favors a small increase in the “fresh” state of the Apple production  
473 variable (+2%, +1.4%, and +0.2% respectively). Given the very limited effect of the scenario  
474 on the Apple production variable among all participants, we can say that participants agree on  
475 this effect.

476

#### 477 **4. Discussion**

478 In a first section, we discuss how this study of ambiguity in socio-ecological systems may be  
479 of interest to those interested in landscape ecology applied to agriculture. In the second section,  
480 we discuss alternatives to ambiguity modelling. In the final section, we discuss the difficulties  
481 involved in participatory BBN modelling regarding stakes and time involved for participants.

482

##### 483 4.1 Ambiguity in landscape effect

484 Our participatory BBN approach was successful in representing and analyzing ambiguity  
485 among stakeholders. Regarding our specific case study, we showed that stakeholders disagree  
486 on the effect of the landscape on insects. This variability is consistent with Bianchi et al.’s  
487 (2006) synthesis mentioning variability in the measurement of landscape effects from  
488 increasing or neutral to decreasing natural enemies’ populations. The relation between natural  
489 enemies enhanced by the landscape and benefit from pest control is more and more widely  
490 challenged in the agroecology literature (e.g. Chaplin-Kramer et al. 2011, Tschardt et al.  
491 2016). In this regard, our results clearly show that the stakeholders actually agree that the  
492 landscape effect has a low impact on apple production. We were able to get new insight on why  
493 farmers did not previously mention any effect of the landscape on natural enemies, whereas  
494 landscape ecology findings regularly do. Even though landscape ecologists may measure more  
495 activity by natural enemies in relation to more complex landscapes, local stakeholders do not  
496 perceive a significant effect of this phenomenon on farms’ economic results. This sheds light  
497 on an important distinction between ecological function and ecosystem services (de Groot et al.  
498 2010). It stresses that, even though landscape ecologists may identify a correlation between a

499 more complex landscape and some useful insects (Bianchi et al. 2006), they identify an  
500 ecological function and not an ecosystem service of pest control to farmers. Our study suggests  
501 that this relation between ecological function and ecological benefits to farmers is far from  
502 obvious. It questions the local feasibility of designing pest-suppressing landscapes as long as  
503 such causality is not identified. This is in line with some scholars who challenge ecologists to  
504 make biodiversity useful for farmers (Letourneau and Bothwell 2008). It explains why local  
505 stakeholders may be resistant to such an innovation approach in pest regulation, because they  
506 do not think it will bring any significant benefit. It suggests that landscape ecologists should  
507 study more explicitly the relation between ecosystem functions stimulated by landscape  
508 complexity and benefits farmers may obtain from them.

509

#### 510 4.2 Modelling alternatives to ambiguity exploration

511 Other modelling approaches could have been considered to explore ambiguity between  
512 stakeholders. Consensus analysis (Romney et al. 1986) or Q methodology (Stephenson 1953)  
513 are statistical methods designed to explore the subjectivity of different stakeholders. They are  
514 based on each stakeholder answering a questionnaire (consensus analysis) or ranking a set of  
515 assertions (Q methodology) in order to identify groups of stakeholders that are similarly minded  
516 about a topic. These two methods deal with ambiguity because their aim is to identify different  
517 groups with similar representations on a topic. Stone-Jovicich et al. (2011), for example, used  
518 consensus analysis to compare the mental models of two types of stakeholders in a river  
519 catchment in South Africa. However, they do not detail the causal relationships between  
520 variables involved in a topic. In particular, they do not explore in probabilistic terms how each  
521 variable behaves for each stakeholder. In this regard, our approach focuses on each individual  
522 representation of these probabilities, whereas the two other methods look for group similarities  
523 and differences. Depending on the objective of the research, whether focused on comparing  
524 detailed individual representations of a system or grouping similar individuals sharing similar  
525 representations, BBN or other methodologies mentioned here may be preferred. Application of  
526 all three methods on a similar case study could be useful to compare their respective advantages  
527 and efficiency in exploring ambiguity.

528

529 The methodology proposed in this paper supposes that it is feasible to reach -together with  
530 participating stakeholders- a consensual conceptual model of the socio-ecological system at  
531 stake. And what if such consensus is not possible because some stakeholders disagree on some  
532 components to be included in the conceptual model? In other words, how can we deal with

533 ambiguity about the structure of the conceptual model? First, structural ambiguity of the  
534 conceptual model could be conserved by maintaining in parallel two or several conceptual  
535 models at the same time. Each conceptual model could be translated into a BBN and each BBN  
536 parametrized by each stakeholder. A similar scenario could be applied to each BBN, allowing  
537 to explore the impact on the components on which stakeholders disagree. An alternative option  
538 could be to explore individual mental models of stakeholders. Carley and Palmquist (1992)  
539 proposed a method to elicit and compare individual mental models through network analysis  
540 and statistical testing for similarities and differences in the content and structure of mental  
541 models. Rather than being statistically analyzed, ambiguity could also be sorted out through  
542 dialogical learning between stakeholders (Brugnach et al. 2011). Indeed, mental models of  
543 disagreeing participants could be directly introduced, discussed and compared by stakeholders  
544 themselves in a collective workshop. According to our knowledge, this latter approach remains  
545 to be tested and documented. Finally, another approach to manage this ambiguity could rely on  
546 the possibility to bring external expertise in case the uncertainty would be epistemic (when  
547 more information reduces the uncertainty). Indeed, in some cases, invited or external expertise  
548 can solve the problem of which stakeholder's representation of a system is correct or not  
549 (Etienne et al. 2011, Halbrendt et al. 2014).

#### 550 4.3 Stakes and time constraint in participatory BBN modelling

551 Another challenge regarding this approach is the time involved in participatory BBN. Each  
552 stakeholder had to mobilize around 12 hours for the whole process (twice three hours for the  
553 consensual conceptual model construction, three hours to arrive at the common Bayesian net  
554 structure, two hours to elicit the CPT, and one hour for scenario exploration). This is quite a  
555 significant amount of time for each stakeholder. In our case study, probably because the stakes  
556 were low, we experienced no major controversies or disagreement when constructing the  
557 conceptual model of the socio-ecological system and the Bayesian net structure. For the same  
558 reason however, we experienced some stakeholder fatigue and difficulty in mobilizing them at  
559 the end of the modelling process. The time constraint has to be put into perspective with the  
560 importance of what is at stake for the participants. In the case of serious disagreement among  
561 stakeholders, it could have been much more time-consuming because each step could have  
562 involved much more discussion to reach consensus. However, if stakes had been high,  
563 willingness to participate would have probably been higher and stakeholders keener to invest  
564 time and energy in a motivating topic. The time constraint is also quite significant in the  
565 probability elicitation step, which may be demanding (Düspohl et al. 2012). Shaw et al. (2016),  
566 for example, mentioned that a probability elicitation step with one expert required more than

567 five hours to answer 120 probabilities, which is way more than what was needed in our  
568 elicitation process. Our opinion is that, because stakeholders were involved in each step of the  
569 construction process, from the initial question to scenario exploration, this favored a clear  
570 understanding and appropriation of the model. Such observation argues in favor of stakeholder  
571 participation all along the participatory BBN modelling approach, but this is never undertaken  
572 according to Düsphohl et al. (2012). The participants also mentioned that co-constructing step  
573 by step a common framework of understanding helped them to understand other participants’  
574 perspectives and sometimes even build new knowledge. This learning effect has already been  
575 stressed in the case of other modelling approaches involving representation elicitation where  
576 interactions between stakeholders favored a shared mental model of a socio-ecological system  
577 (Mathevet et al. 2011).

578

## 579 **5. Conclusion**

580 BBNs are well known for their capacity to deal with ontological uncertainty. However, the  
581 participatory BBN construction process are normally not specifically exploring the  
582 uncertainties which are related to ambiguity. Eliciting and eventually sorting out ambiguities  
583 can be critical when it comes to participatory processes. We introduced in this paper an  
584 approach alternating collective and individual steps to build individual BBNs for different  
585 stakeholders about the same socio-ecological system. This participatory BBN modelling  
586 demonstrated its ability to capture different stakeholders’ representations and thus detail  
587 ambiguity about how a socio-ecological system may function. This participatory BBN  
588 modelling approach engaged stakeholders in all the steps. Comparison of stakeholders’ BBNs  
589 enabled visualization of each stakeholder’s subjectivity and identification of areas of agreement  
590 or disagreement about the way stakeholders think the socio-ecological system works and how  
591 it reacts to an exploratory scenario. This method applied to a case study regarding different  
592 representations of the effect of the landscape on natural enemies within orchards led to  
593 understanding the underlying reason for differing representations between local stakeholders  
594 and landscape ecology findings. This method is an innovative approach to sorting out  
595 ambiguities among stakeholders while conserving ontological uncertainties. It could be used in  
596 any context facing apparently contradictory representations among different stakeholders about  
597 a socio-ecological system. It would be particularly interesting to eventually use this method, if  
598 needed, for use in controversial situations where higher stakes may necessitate a detailed  
599 understanding of each stakeholder’s representation of an issue.

600

601

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611

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