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Title: Modeling biodiversity change in agricultural landscape scenarios - a review and prospects for future research

Authors: Pierre Chopin^{1,2}, Göran Bergkvist¹, Laure Hossard³

Affiliations:

¹Department of Crop Production Ecology, Swedish University of Agricultural Sciences, Uppsala, Sweden

²ASTRO Agrosystèmes Tropicaux, INRA, 97170, Petit-Bourg, Guadeloupe, France

³UMR951 Innovation, INRA, Univ Montpellier, F-34060, Montpellier, France

E-mail addresses: pierre.chopin@slu.se; goran.bergkvist@slu.se; laure.hossard@inra.fr

Name and mailing address of corresponding author: Pierre Chopin, Ekologikum, Ulls Väg 16, S-75651 Uppsala , pierre.chopin@slu.se, Tel: +46 762323274

1 **Abstract**

2 Increased intensity of agriculture and landscape homogenization are threatening biodiversity in
3 landscapes. We reviewed 67 case studies addressing the impact of agriculture on biodiversity in model
4 based scenario approaches and compared the information they provide on biodiversity, spatial
5 characteristics, scenarios, and landscapes. We found an overall large diversity of approaches that we
6 summarized statistically into six groups. “Biodiversity based agent based models”, “Expert based
7 exploration of land use change with GIS” and “Land use approaches of biodiversity with spatially explicit
8 statistical model” are specialized biodiversity studies with high complexity in terms of biodiversity
9 modelling with agent-based models or mechanistic models. On the other hand, “Bioeconomic modelling
10 of policy impacts in favor of restoration of beneficial habitats”, “Participatory simulation studies of
11 landscape futures” and “Large scale multi criteria studies of innovative scenarios with optimization” do
12 not consider species’ behavior or landscape configuration, but do address a large range of
13 socioeconomic and environmental issues. As a contribution to developing quantitative and policy-
14 relevant biodiversity conservation studies in landscape, we present the advantages and disadvantages of
15 each approach. We then suggest combining different approaches, particularly with the use of agent-
16 based models and mechanistic models, integrating spatially explicit drivers of biodiversity change and
17 the socio-economic context of farming in a participatory manner. We give recommendations on the
18 inclusion of more taxa in future studies and collaboration between scientists from different disciplines
19 to develop innovative solutions that can halt the biodiversity decline in agricultural landscapes.

20 **Keywords:** species conservation; land use change; farm management; landscape configuration;
21 biodiversity-ecosystem functioning; wildlife-friendly farming

22 1. Introduction

23 Conservation of biodiversity (genes, species, and ecosystems) is considered by many to be an ethical
24 imperative (Dramstad and Fjellstad, 2011). Biodiversity also supports 'ecosystem services', i.e.,
25 ecological processes and functions that sustain and improve human wellbeing (Daily 1997). Biodiversity
26 can contribute to the provision of ecosystem services such as pollination, biological regulation of pests
27 in agroecosystems, and provision of food and feed (Duffy et al., 2017). The ecosystem services provided
28 by biodiversity can help maintain the productivity of cropping systems, while reducing the use of
29 external inputs responsible for several negative environmental impacts in agricultural landscapes.
30 Agricultural landscapes are mosaics of farmers' fields, semi-natural habitats, human infrastructure (e.g.,
31 roads), and occasional natural habitats (Marshall 2004) that together provide a range of services such as
32 provision of food and fiber, carbon sequestration, nutrient recycling and cultural services. Hence, by
33 definition, an agricultural landscape can cover an area as small as a few fields or can encompass an
34 entire continent. Conserving biodiversity in agricultural landscapes can help provide ecological,
35 economic, and social benefits (Estrada-Carmona et al., 2014).

36 However, the benefits provided by landscapes are decreasing because of the current decline in species
37 and individuals at large scales (Butchart et al., 2010). Agriculture is one of the main activities responsible
38 for this decrease in landscape biodiversity (Isbell et al., 2017; Kehoe et al., 2017). Over the past decades,
39 the expansion of agricultural land, the decline in landscape heterogeneity, the increased use of
40 fertilizers and pesticides, and the conversion to systems with low crop diversity, have had major effects
41 on global biodiversity (Emmerson et al., 2016, Tschardt et al., 2005). These changes are also
42 decreasing the provision of services to humanity (Bianchi et al., 2006, 2013). For instance, farmland
43 birds are experiencing large declines in all parts of the world, due to agricultural intensification causing
44 habitat losses (Laaksonen and Lehikoinen, 2013; Stanton et al., 2018). Populations of farmland birds,
45 such as skylarks (*Alauda arvensis*), have been massively reduced, resulting in an associated decrease in
46 the ecosystem services they provide, e.g., in terms of reduction of weed seeds (Eraud et al., 2015). A
47 similar reduction in species richness has been found in aquatic systems, e.g., stream invertebrates have
48 been reduced by up to 42% in Europe and Australia, largely due to pesticide use (Beketov et al., 2013).
49 The practices that are negative for biodiversity are a result of intensification of production that is largely
50 induced by global drivers, such as market demand for more and cheaper commodities (Lenzen et al.,
51 2012; Weinzettel et al., 2013), and recent policy for production of bioenergy on agricultural land
52 (Immerzeel et al., 2014).

53 Fortunately, agricultural landscapes can be designed and managed to host wild biodiversity of many
54 types, with neutral or even positive effects on agricultural production and livelihoods (Altieri 1999;
55 Scherr and McNeely, 2008). Different landscape-level strategies to find compromises between
56 production and conservation have been widely discussed, the most prominent debate being on land
57 sharing compared with land sparing strategies (Green et al., 2005; Phalan et al., 2011). These strategies
58 can be discussed at different spatial scales ranging from field level (e.g., Colbach et al., 2018) to global
59 level with the creation of biodiversity protection areas such as conservation concessions or indigenous
60 reserves world-wide (Watson et al., 2014; Hoffmann et al., 2018). Since some ecological impacts of
61 agriculture on biodiversity occur at a level above field scale, it is also important to study biodiversity at a
62 larger scale (Pelosi et al., 2010). The relative area and spatial configuration of agricultural and natural
63 components are key landscape design issues (Auffret et al., 2015).

64 When studying the future of agricultural landscapes for improved consideration of biodiversity aspects,
65 the socioeconomic aspects of landscapes needs to be accounted for by planners (Benoît et al., 2012).
66 Agricultural landscapes are complex adaptive socioecological systems structured and managed by

67 various stakeholders including for instance farmers, local and regional governments, and non-
68 governmental organizations (NGOs) (Biggs et al., 2013). This increases the complexity of the biodiversity
69 issue and the number of drivers that determine the landscape characteristics. Such drivers can be
70 socioeconomic, political, technological, natural, or cultural (Brandt et al., 1999). None of these drivers
71 are fixed in time and space, or independent from each other, and they are evolving continuously. The
72 change in drivers modifies the state of biodiversity in landscapes. One such change is the
73 implementation of agri-environmental schemes for the protection of biodiversity in the European
74 Common Policy (CAP).

75 In order to monitor the changes in biodiversity, scientists are developing methods for simultaneously
76 studying landscape changes that could affect biodiversity within agricultural landscapes and ecosystem
77 services (e.g., production of food, esthetic value). Most of these methods are based on scenarios, which
78 is a powerful tool to envision how biodiversity might respond to different pathways of future human
79 development and policy choices (Díaz et al., 2015). In models, the landscape and processes that
80 determine biodiversity are simplified in a certain way by the adoption of different modeling approaches
81 for designing agricultural landscapes and assessing changes in biodiversity (e.g., Topping 2011; Drum et
82 al., 2015; Kirchner et al., 2015). The objectives and associated methods of such studies may contribute
83 to different assessments of the impacts of agricultural development on biodiversity in landscapes. It is
84 possible to gain more insights into the nature and complexity of approaches by focusing on their key
85 characteristics: the spatial characteristics and landscape representation, the type of biodiversity studied,
86 the scenario techniques, and the type of models used to design and assess landscapes.

87 Our objectives with the current review were to describe the diversity of approaches for scenario analysis
88 of biodiversity-related challenges and to suggest guidelines for methodological improvements. To
89 achieve these objectives we, i) reviewed existing studies in the literature and compared the landscape,
90 the spatial emphasis, the scenario characteristics, and the type of models used, ii) identified links
91 between these characteristics, iii) grouped the studies to identify common approaches, and finally iv)
92 scrutinized current methods and pathways in order to identify ways to improve approaches to modeling
93 biodiversity change in landscapes.

94 **2. Material and methods**

95 2.1. Literature research

96 We conducted the literature research in a systematic way by formulating a search equation in ISI Web of
97 Knowledge. The equation was divided into four topics: i) model, ii) scenarios, iii) landscape and iv)
98 agriculture. According to the IPBES (2016), scenarios and models can provide an effective means of
99 addressing relationships between nature, nature's benefits to people, and, good quality of life. They
100 have a complementary role with scenarios describing possible futures for drivers of change, and models
101 translating them into projected consequences for natures and benefits for people. Scenarios are not
102 predictions of what will happen, but are projections of what might happen, or could happen, given
103 certain assumptions about which there might be great uncertainty (Börjeson et al., 2006). For each
104 topic, we identified potential synonyms to build our equation (Equation 1). For the model topic, only the
105 keyword "Model" was used. Scenarios refer to the construction of different "alternatives" to modify the
106 structure of the system represented. We introduced different scales ("landscape", "watershed" and
107 "water catchment") in the equation to represent landscapes. Watershed and water catchment were
108 introduced because they are important scales in the management of water in landscapes coupled to
109 biodiversity issues. We did not introduce the word "region", because it vastly expanded the search
110 results by selecting many papers stating only their area of study, rather than being performed at the
111 regional level. We introduced the terms "agri*", "agro*", "crop*" and "farm*" to refer to agriculture

112 (e.g., agronomy, agroecology, agriculture, crops, cropping systems, farm or farming systems), in order to
113 capture the diversity of agricultural use of land. Biodiversity was not included in the equation, because
114 many studies focus only on some species without mentioning the word “biodiversity”. Instead of
115 widening the equation by introducing all types of taxa, we decided to introduce an ad hoc filter of the
116 list of papers. The equation was as follows:

117 Equation 1:

118 **TS = (model * AND ((scenar * OR alternativ *) AND (landscape * OR watershed *
119 OR (water NEAR catchment *))) AND (agri * OR agro * OR crop * or farm *)))**
120

121 The literature search was closed on May 4, 2017 and the results encompassed 1975 papers (Figure 1).
122 Papers that were more recent were not included.

123 <Insert Figure 1>

124 We then followed a discarding procedure in which we excluded papers that did not include agriculture
125 (e.g., forest studies only) or scenario (e.g., model calibration/validation only), that were not at landscape
126 scale (e.g., field or farm only), that did not use models (e.g., expert-based knowledge only), or without
127 any case study (e.g., model calibration, validation) and that did not include any biodiversity conservation
128 issue (Figure 1). The order of filters modify the number of papers along the discarding procedure, but
129 not in the final list which comprise 65 papers for a total of 67 case studies, as in one paper three case
130 studies were developed (Groot et al., 2009). These studies came from 33 peer-reviewed journals and
131 were conducted in 17 different individual countries, with two conducted at the European level
132 (Supplementary material).

133 We described each study with categorical variables (Table 1). The few quantitative variables (e.g., area
134 studied) were turned into ordinal categorical variables. The description of each of the 67 studies was
135 based on 13 categorical variables (4 ordinal, 9 nominal) grouped into five categories: 1) “Spatial
136 characteristics”, gathering variables describing the extent of the study area and the spatial scales
137 considered. 2) “Landscape”, describing the representation of landscape in terms of agriculture and the
138 change considered in the landscape. 3) “Biodiversity category”, gathering information regarding the taxa
139 modelled and the processes driving the change in taxa abundance. 4) “Scenario”, grouping information
140 regarding the type of scenario developed and the process to develop them. 5) “Model”, describing the
141 type of model used to produce landscape and assess the biodiversity change. We describe the
142 categorical variables below.

143 2.2.1 Spatial characteristics

144 2.2.1.1 Extent

145 The extent is the size of the landscape unit included in the study. The extent of the landscape has
146 various effects on the processes studied. For instance, Bianchi et al., (2006a) state that diversified small
147 landscapes are more effective in pest control than large landscapes. We categorized “extent” into three
148 subcategories (“local”, “national/local”, “global/supranational”), as suggested by van Notten et al.,
149 (2003). These subcategories corresponded to studies on landscape areas <100 km², 100-1000 km², and
150 >1000 km², respectively.

151 2.2.1.2 Spatial scale

152 Different procedures can help change the information from one scale to another to provide an indicator

153 of the impacts of change such as sum, interpolation, or other mathematical formula (Volk and Ewert,
154 2011). Here, we only considered the number of scales involved in the transfer of information.
155 “Landscape scale only” corresponds to processes simulated at the landscape level only, “from lower
156 level to landscape level” corresponds to two different scales, and “multi-scale” corresponds to more
157 than two scales involved in the transfer of biodiversity information at landscape level (Chopin et al.,
158 2017). Generally, the scale at low level corresponds to fields or pixels, intermediate scale can be farm or
159 hydrological response unit, and large scale can be a water catchment, several catchments, or an
160 administrative area such as a county, a country, or a continent (e.g., the European Union).

161 2.2.2 Landscape

162 2.2.2.1 Agricultural land use precision

163 The landscape represented in the different studies consisted of different land uses. The detail with
164 which these agricultural land uses were described in the selected studies varied from a broad
165 categorization to a very precise description. We divided the variable “land use” into two subcategories.
166 In the subcategory “land cover”, the land use was described roughly as “grassland”, “arable land”,
167 “forest “ or similar and did not describe the species present (Drum et al., 2015). For “land cover”, there
168 was generally only one associated management parameter across the studied landscape, such as one
169 cattle density for grassland. We called “crops” the agricultural land use for which crops at plot level are
170 known and generally, several management systems of the same crop are accounted for (e.g., intensive
171 or extensive wheat production).

172 2.2.2.2 Change in agricultural landscapes

173 The selected studies described various characteristics of agriculture responsible for the change in
174 biodiversity: i) a change in activity of cropping or land cover, and/or ii) a change in intensity, which
175 corresponds to the type of management (e.g., pesticide application, soil management, etc.) applied to
176 the crops or land cover types. For instance, Dormann et al., (2008) show that hoverflies and spiders are
177 more affected by land cover than crop management, while the opposite trend is observed for birds,
178 bees, bugs, and beetles in Europe. We considered these two types of processes in the variable “change
179 in agricultural landscapes”: “Change of activity”, i.e., reorganization of current uses in the landscape and
180 “change of intensity”, i.e., a change of land use intensity not affecting the land cover. These two changes
181 can also be simultaneously changed in the simulations and were then categorized as “change of activity
182 and intensity”.

183 2.2.3 Biodiversity

184 2.2.3.1 Spatially explicit processes driving biodiversity change

185 An important characteristic of the study of landscape change linked with biodiversity is the spatial
186 organization of landscape driving the abundance of taxa. Several spatially explicit processes, called
187 landscape factors by ecologists (Bianchi et al., 2006b), influence biodiversity and are related to the
188 organization of the landscape, which is the spatial location of the different types of land use within the
189 landscape. In the literature, the spatial organization is referred to as “landscape structure”,
190 “aggregation”, “arrangement”, or “configuration”, but these terms often describe the same property of
191 the landscape. We chose to represent spatial organization with a binary variable with two levels
192 (“yes”/“no”), indicating whether or not spatial organization of landscape was included in a study.

193 194 2.2.3.2 Species behavior

195 The variable “species behavior” describes the integration of variables linked to the biology of species in

196 the modelling of biodiversity. Such variables include e.g., foraging or nesting requirements of birds
197 (Cardador et al., 2015). Potential competition for land area also appears between species and can be
198 integrated, e.g., co-specific abundance of species where the level of one species population is linked to
199 that of another (e.g., Casado et al., 2014). For plant species diversity, suitability or preferences for some
200 biophysical conditions were included in this species behavior variable. If any process characterizing
201 landscape suitability for a given species or behavior was included in the study, the variable value was set
202 as “yes”, otherwise it was “no”.

203 2.2.3.3 Number of taxa

204 About 66% of the studies considered a sole taxon as an indicator of the general state of the system, 13%
205 considered several taxa, and the remainder considered general biodiversity (see Supplementary
206 material). The most common taxon used as an indicator of biodiversity was birds, in 22 studies, most of
207 them focusing on farmland birds (e.g., Guillem et al., 2015). Birds were often considered indicators of the
208 state of biodiversity even if only one species was studied (e.g., skylarks in Guillem et al., 2015). However,
209 some studies included several species with contrasting niches (e.g., five farmland birds (Brandt and
210 Glemnitz, 2014)). Insects, such as grasshoppers (Steck et al., 2007) or bees (Baveco et al., 2016), fish
211 (Weinberg et al., 2002), bivalvia (Randhir & Hawes 2009), mammals (Jepsen et al., 2005) and plants
212 (Egan and Mortensen, 2012) were also used as single taxon indicators of biodiversity. In our set of 67
213 studies, only nine included more than one taxon. For instance, Gottschalk et al., (2007) focused on
214 changes in birds and carabids. Finally, in some studies, biodiversity was assessed in a general manner.
215 Dormann et al., (2008) focused on seven groups of organisms (plants, birds, spiders, wild bees, ground
216 beetles, true bugs, and hoverflies) to depict the impact of landscape change on biodiversity. We
217 categorized species diversity into the subcategories “single taxon”, “set of taxa”, or “general
218 biodiversity”.

219 2.2.4 Scenario

220 2.2.4.1 Participatory

221 Participatory modelling is a tool to enhance stakeholder knowledge and understanding of a system and
222 to clarify the impacts of changes to help decision making (Voinov and Bousquet, 2010). There are
223 different typologies of participation, with increasing degrees of engagement of stakeholders in scenario
224 studies (Reed 2008). Here, we used a binary variable for which the value was set as “no” when there
225 was no stakeholder engagement in the study or simply an expert consultation phase, and “yes” when
226 there was active involvement of stakeholders in the scenario definition or assessment.

227 2.2.4.2 Issues addressed

228 The importance of biodiversity in the selected studies varied from studies that focused only on
229 biodiversity change in the landscape to broader studies where multiple issues were targeted.

230 To display this range, we categorized this variable into three classes: “Biodiversity-centered”, depicting
231 studies that only addressed biodiversity change; “biodiversity coupled to one or two other issues”,
232 gathering studies where biodiversity was addressed coupled mostly to economic or food production
233 aspects with e.g., a focus on land sparing vs. land sharing strategies (e.g., Egan and Mortensen, 2012);
234 and “multi-issues”, gathering studies in which an integrated assessment was performed with many
235 indicators, including e.g., food provision, economic viability of farming, water quality and quantity,
236 esthetic value (e.g., Bryan et al., 2011; Gutzler et al., 2015) (See Supplementary material).

237

238 2.2.4.3 Drivers of landscape change

239 Different types of drivers can modify the landscape, thus potentially affecting biodiversity. Among these
240 drivers we identified policy change, biophysical change, and direct land conversion. Some studies
241 examined the impact of only one driver, while some studies considered a combination of several drivers
242 of change. We categorized the studies into those with a “single driver” and those with “multiple
243 drivers”.

244 2.2.4.4 Scenario type

245 We classified this variable into three categories: “simple change”, “system change”, and “transformative
246 change” scenarios following existing typologies of change (e.g., Roggema and Dobbelsteen, 2012). The
247 level “simple change” mostly concerns incremental change of landscape with, for instance, conversion
248 scenarios in which a given area was turned into another land use based on some simple rules (e.g., the
249 authors decided to switch a given area from pasture to bioenergy). In “system change” scenarios, also
250 defined as transitional scenarios, modification of a set of known biophysical and socio-economic
251 variables allows the transition of the system, such as a change of subsidies. In this type of scenario,
252 several parameters were modified to produce new landscapes, which would imply a change in
253 biodiversity. Finally, “transformative” scenarios are descriptions of change with storylines where
254 complex scenarios of high complexity are developed and translated to model parameterization
255 (Cardador et al., 2015).

256 2.2.5 Modeling

257 In the selected studies, models were used to i) design new agricultural landscapes and/or ii) assess the
258 change in biodiversity in these landscapes. We also included studies for which models to design
259 landscapes were not used, as our main focus was on the assessment of biodiversity.

260 <Insert Table 1>

261 2.2.5.1 Model to design landscapes

262 We divided the type of model used to design landscapes into five categories: “Optimization model”,
263 “agent-based model”, “mechanistic model”, “statistical model”, and “no model for design” (Table 1):

- 264 • **Optimization model.** In most approaches, the decision-making process of farmers was the core
265 process modelled. It assumes that individual farmers make land use decisions to maximize their
266 utility, very often represented as their revenue, under resource constraints, mainly land and
267 labor (see reviews by Janssen and van Ittersum (2007) and Reidsma et al., (2012)). Optimization
268 can be at different scales, e.g., farm level (Weinberg et al., 2002) or landscape level (Chopin et
269 al., 2015). In optimization models, farmers’ decisions are simulated and produce new
270 agricultural landscapes. For these newly produced landscapes, other types of model are used to
271 assess the level of biodiversity.
- 272 • **Agent-based model (ABM).** An ABM describes decision making by several entities, such as
273 farmers, that interact across time through individual transactions in a market with potential
274 spatial interactions (Bousquet and Le Page, 2004; Kremmydas et al., 2018). It is specifically the
275 interactions among agents that make the “agent-based model” different to the “optimization
276 model” where agents are simulated individually (Nolan et al., 2009).
- 277 • **Statistical model.** Describes land use changes using probabilities of change of land use from one
278 category to another based generally on historical changes (Verburg et al., 2004). Such models

279 include cellular automaton (Campagne et al., 2009), Markovian models (Coppedge et al., 2007),
280 or regression models linking land use with different biophysical and/or socioeconomic variables
281 at local level (e.g., soil, rainfall, land tenure) or global level (elevation of temperature, demand
282 of commodities), which is the case with the widely used CLUE model (Veldkamp and Lambin,
283 2001).

- 284 • **Mechanistic model.** Models system functioning by a set of equations linking the inputs of the
285 system (e.g., crop, fertilizers) with outputs (e.g., yields, development of habitats).
- 286 • **No model to design.** In some studies, no model is used to describe the change in landscape. The
287 change in landscape is driven by expertise or prior studies that describe changes in land use
288 types.

289 2.2.5.2 Model to assess biodiversity

290 We gathered the type of model used to assess biodiversity into five categories, namely “agent-based
291 model”, “mechanistic model”, “statistical model”, “landscape indicators”, or “habitat suitability”.

- 292 • **Agent-based model.** In the case of assessment of biodiversity change, the agent-based model
293 simulates changes in populations and communities by following individuals in time and space
294 and their associated properties (DeAngelis and Grimm, 2014). Each individual has a set of state
295 variable or attributes and behavior. State variables can include spatial location, physiological
296 traits, and behavioral traits. These attributes vary between individuals and can change in time
297 and space. Behaviors can include growth, reproduction, habitat selection, foraging, and
298 dispersal. Running such a model provides information regarding population dynamics and
299 changes in abundance across space and time.
- 300 • **Statistical model.** It describes change in biodiversity abundance as an equation linking
301 abundance as independent variable with a set of explanatory variables at landscape level,
302 including e.g., land use within a certain radius or distribution of patches.
- 303 • **Mechanistic model.** Also called a process-based model, it links the change in biodiversity state
304 to the system state through a range of equations.
- 305 • **Landscape indicators.** These variables provide indications on the state of biodiversity, usually
306 with a simple formula with no explicit model structure.
- 307 • **Habitat suitability.** Different habitat values are attributed to all land uses/land cover or crops in
308 a region and the increase in habitat induces the increase in biodiversity (and vice versa). The
309 higher the habitat value, the higher the increase in biodiversity. Bird abundance values for each
310 habitat in the models included here were mostly obtained from previous studies.

311 In Supplementary material, we provide a list of examples for each category of model used to design
312 landscapes and to assess biodiversity, extracted from our list of case studies.

313 2.3. Statistical Analysis

314 <Insert Figure 2>

315 To analyze the dataset, we used four types of statistical approaches (Figure 2). First, we analyzed the
316 relationships among the 13 initial variables that described the case studies. Second, we conducted
317 multi-correspondence analysis (MCA) to decrease the complexity of the dataset. Third, we selected the
318 main components from the MCA to group studies based on their similarity using ascending hierarchical

319 clustering (AHC). Fourth, we used a regression tree (CART) to describe the main differences between
320 groups.

321 2.3.1. Step A: Correlation study

322 Among the 13 categorical variables, nine were nominal variables and four were ordinal variables. The
323 bivariate association among the ordinal variables was tested using Goodman-Kruskal's gamma for
324 ordinal variables in R package DescTools 0.99.24 (Signorell 2018). Goodman-Kruskal's gamma measures
325 correlations among variables (Pearson 2016), with values from -1 (negative association) to $+1$ (positive
326 association). Association among nominal variables and between nominal and ordinal variables was
327 assessed using the Chi-square. If the null hypothesis is rejected, the strength of the association is
328 assessed with Cramér's V (Signorell 2018), a number between 0 and 1 that indicates how strongly
329 one nominal and one ordinal variable, or two nominal variables, are associated. If the results denote a
330 significant association between variables, this means that the pattern of distribution of studies between
331 two variables can present some very low numbers.

332 2.3.2. Step B: Multi-correspondence analysis (MCA)

333 In order to identify trends in terms of approaches to model-based scenario analysis of biodiversity
334 change in agricultural landscape, we grouped the existing approaches based on their level of similarity.
335 We started by reducing the number of variables used in our analysis, through performing MCA on the 13
336 variables using the FactoMineR package (Husson et al., 2015) in R software (R Development Core Team
337 2008). MCA is a data analysis technique for categorical data, used to detect and represent underlying
338 structures in a dataset. It is an alternative to principal component analysis (PCA) for categorical variables
339 including both nominal and ordinal variables. The first components, accounting for as much of the
340 variability in the data as possible, summarize the greatest amount of information from the dataset.

341 2.3.3. Step C: Ascending hierarchical clustering (AHC)

342 MCA was used as a method for de-noising data by producing non-correlated components and then for
343 performing hierarchical clustering analysis of studies based on these components. We selected the
344 components derived from the 13 variables that explained 70% of the variance of our sample of case
345 studies (Higgs 1991). Ascending hierarchical clustering was performed on these components. We used
346 Ward's method to classify the studies into groups in order to minimize the intra-group variability and
347 maximize the inter-group variability. With this method, we did not need to pre-select a given number of
348 groups. We then characterized the groups by the main categories of the categorical variables (Husson et
349 al., 2010). To evaluate the relationship between these, we compared their proportions through a
350 statistical test based on the hypergeometric distribution. The null hypothesis was that the proportions
351 of each variable treatment should be equal in groups (Lê and Worch 2015). Categories of the variables
352 significantly linked to the groups were identified with p -value and V value (Husson et al., 2011). The
353 overrepresented categories of all categorical variables were thereby identified, with values ranging from
354 2 to 3 indicating "slight overrepresentation", 3-5 "moderate overrepresentation" and >5 "important
355 overrepresentation" (Husson et al., 2011). Only the overrepresented categories characterizing the
356 groups are described in the results section, to ease interpretation.

357 2.3.4. Step D: Regression tree

358 In order to identify the initial variables that best contributed to the partitioning of the set of studies, we
359 performed a regression tree. Classification and regression trees (CART) are part of a recursive
360 partitioning method. We used it here to model the group classification from the AHC as a function of our
361 13 initial variables. CART provided several advantages considering our dataset: (1) nonparametric basis,

362 (2) no implicit assumption of linearity, and (3) simplicity of results for interpretation. CART tools are
363 available in the R package “rpart” (Therneau and Atkinson n.d.), based on the function developed by
364 (Breiman 1984). The regression tree produces threshold values of initial variables that allow allocation of
365 studies to a given new group called “leaf”. The classification of studies in the leaves is compared with
366 groups from the AHC. Tree depth level was limited here to three levels and minimum leaf size to five
367 studies, in order to avoid overfitting. Tree performance was tested by calculating Pseudo-R² and by
368 cross-validation with the “rpart” algorithm.

369 3. Results

370 3.1. Crossing of variables describing approaches

371 Overall, 19 pairs of the variables described in Table 1 were significantly correlated (Table 2). The variable
372 “issues addressed” was positively correlated with “extent” of the study area, i.e., the larger the size of
373 the landscape unit studied, in general the more issues investigated. In most large-scale studies, “species
374 behavior” was not accounted for. The variable “crops” was accounted for in all studies with several
375 “spatial scales”, but almost never in studies at “landscape level only” (n=6). The one exception was a
376 study by Bathgate et al., (2009) that targeted farming system change directly relating to a change of
377 pasture management, without accounting for the farm-scale level (Table 2).

378 <Insert Table 2>

379 “Species behavior” was not accounted for in studies comprising a “set of taxa”, probably due to the
380 need for very complex models to address such processes, and particularly when the “issues addressed”
381 were numerous. Similarly, “spatially explicit process driving biodiversity change” tended not to be
382 accounted for in studies targeting “multi-issues” (1 study out of 15).

383 The inclusion of “participatory” was related to a way to build scenarios with “transformative change”,
384 while it was poorly used for “simple change” of land for biomass production. Similarly, transformative
385 scenarios were often associated with “multiple drivers” of landscape change (Table 2).

386 <Insert Figure 3 and 4>

387 Figures 3 and 4 illustrate the gaps in current methodological approaches by crossing sets of variables
388 with the type of “model to design landscapes” and the type of “model to assess biodiversity”,
389 respectively. It was only when no model was used for the design of landscapes that studies approached
390 the landscape level directly (Figure 3A). All studies with a model approach included different scales,
391 illustrating studies examining changes performed directly at the landscape scale by scientists or
392 stakeholders. Very few studies accounted for more than two scales without a model to design (Figure
393 3A). In most cases (6 out of 8), studies using “mechanistic” and “statistical” models did not consider
394 “cropping systems (Figure 3B). It was only when “mechanistic” models were used that the majority of
395 studies (5 out of 8) used a participatory approach (Figure 3C). The link between “issues” and any
396 particular model was not obvious, but a large proportion of the studies (16 of 25) that did not use a
397 model for design were “biodiversity-centered” (Figure 3D). In all but one case, “agent-based models”
398 and “statistical models” were used to target biodiversity, either “biodiversity coupled to others” or
399 “biodiversity-centered”, and not “multi-issues”. On the other hand, only one study that was
400 “biodiversity-centered” used an optimization model (Figure 3D). Finally, all model types except
401 statistical models were used to develop scenarios with “transformative change”, i.e., complex storylines
402 (Figure 3E). Studies combining “optimization model” for design, and storylines, are very scarce. When
403 “no model to design” was used, “conversion” scenarios or “system change” were used to develop
404 scenarios (Figure 3E).

405 In terms of “model type to assess”, studies using “landscape indicators” did not integrate the behavior
406 of species and those using a “statistical” model did so only in two studies out of 15 (Figure 4A). On the
407 other hand, other models, “agent-based models”, “habitat suitability”, and “mechanistic”, were used to
408 simulate “species behavior” of species targeted. The “general” state of biodiversity was mostly
409 addressed through “landscape indicators” and “habitat suitability” functions (Figure 4B). A
410 “mechanistic” model or “agent-based model” was not used for wide appraisal of biodiversity, but mostly
411 for “single taxon”. “Statistical” models followed a similar trend except for two studies targeting “several
412 taxa” and two others focusing on the “general” state of biodiversity (Figure 4B). In terms of issues
413 targeted, biodiversity in “multi-issues” studies was generally assessed with a “habitat suitability” model
414 or “landscape indicators” (Figure 4C). Furthermore, “landscape indicators” were mainly used in “multi-
415 issues” studies to chart changes in “general biodiversity” in landscape, along with “multi-issues” linked
416 to agriculture. “Habitat suitability” models were used in a wide range of studies, ranging from
417 “biodiversity-centered” to “multi-issues” (Figure 4C). Agent-based models were only used to assess
418 biodiversity change in “biodiversity-centered” studies. Coupling the type of “model to design
419 landscapes” and “model to assess biodiversity” revealed some gaps (Figure 4D). “Statistical models”
420 used to produce landscapes were usually assessed using “habitat suitability” models or “statistical
421 models”. Biodiversity in landscapes produced from “optimization models” was never assessed using
422 “agent-based models”. Biodiversity in landscapes produced with “mechanistic models” was never
423 assessed using “statistical models” in our dataset.

424 3.2 A typology of six diverse approaches

425 The first and the second principal components of MCA explained 24 and 10 % of the variance,
426 respectively. The first component was largely determined by the variables “issues” and “model to assess
427 biodiversity”. The second component was significantly linked to the variable “issues” and to “scales” and
428 the “model to design landscapes” (Supplementary material).

429 <Insert Figure 5 and Table 3>

430 From the AHC, six groups of studies were identified in terms of similarity of individual studies in groups
431 (Table 3) and important inter-class inertia (Supplementary material):

432 **Group 1 (n=9).** In this group, agent-based models were used to simulate the decision-making process of
433 farmers, generally in terms of land cover or crop choice, linked to their resources, behaviors and
434 relationships. These studies encompassed several spatial scales (“multi-scale”), combining (a) the field
435 level at which crops or land cover were allocated (e.g., Schouten et al., 2014) (b) the farm scale, which
436 was the scale at which farmers took decisions regarding their activity and (c) the landscape level, at
437 which the impacts were measured. The agent-based models used encompassed individual-based models
438 simulating the behavior of animals, mostly birds (Guillem et al., 2015) or mammals (Hammershoj et al.,
439 2006) in the landscape and their population dynamic in relation to feeding or reproduction
440 requirements. These studies were all “biodiversity-centered”, focusing on how conservation of species
441 could be achieved (Schmitt et al., 2016) or how predators or invasive species could be limited in the
442 landscape (Hammershoj et al., 2006). All studies in this group focused on the impacts of “simple change”
443 within the landscape (6 studies out of 9) such as direct conversion of land for bioenergy (Gevers et al.,
444 2011) or “system change” (3 studies out of 9) with e.g., a policy change such as a regional groundwater
445 protection strategy (Jepsen et al., 2005).

446 **Group 2 (n=14).** This group gathered approaches of strict assessment of biodiversity change, with eight
447 “biodiversity-centered” studies (e.g., Baveco et al., (2016) on bee exposure to pesticides) and six studies
448 examining “biodiversity coupled to other issues” (e.g., Everaars et al., (2014) on the biodiversity

449 response to increased bioenergy production). In 11 out of 14 studies, “no model” was used to produce
450 landscapes. The studies of landscapes were based on existing landscapes where changes were applied
451 randomly in the landscape, such as the conversion of fields to organic agriculture (Bredemeier et al.,
452 2015). The evolution of biodiversity population was assessed using “mechanistic model” or “habitat
453 suitability” model to assess biodiversity (5 and 7 studies out of 14, respectively). Mechanistic models link
454 the variation of land use area to the population dynamic of species with for instance the change in area
455 of interest for bee foraging (Baveco et al., 2016) or, habitat variation that modifies the species
456 population proportionally, such as the occurrence of sage-grouse with cropland (Smith et al., 2016). All
457 these studies focus on a “single taxon”. Land use was re-organized at low level in 11 studies, mainly
458 through field change (six studies) or pixel change (two studies) with GIS, and consequences were
459 assessed directly at landscape level.

460 **Group 3 (n=14).** In this group, studies use a statistical model or no model to represent the change in
461 “land cover” in agricultural landscape (in 13 out of 14 studies). Usually aggregated land uses are adopted
462 such as grassland, oilseed crops or cereal. The statistical model links the area of each land cover to
463 global drivers, such as the demand for commodities and their associated price by way of regression. The
464 assessment of biodiversity in the landscape is also undertaken using regressions that are built to explain
465 the initial level of population of a given species in relation to the proportion and location of “land
466 cover”. In such regressions, the characteristics of landscapes, such as fragmentation or connectivity, is
467 accounted for in 9 studies that consider “spatially explicit process driving biodiversity change” (e.g.,
468 Blanchard et al., 2015). Some suitability models are also used in some studies. (e.g., Fonderflick et al.,
469 2010). The behavior of species was not accounted for in any of the studies. Most studies (12 out of 14)
470 were biodiversity-centered”, with no pattern regarding the “number of taxa” considered (Table 3).

471 **Group 4 (n=14).** In this group, studies use optimization models (11 out of 14 studies) with a bioeconomic
472 approach at farm or regional level that focus on the impacts of farmers’ decisions on regional crop
473 change and the subsequent impact on biodiversity. In 12 studies, the model integrates a precise
474 description of crops with different management options and the management is linked with the issues
475 targeted. In 12 out of 14 studies, only a few issues were targeted with biodiversity, mostly economic
476 return and production, while only two studies were “multi-issues”. Of the studies in this group, 11
477 targeted policy analysis in “system change” scenarios and three examined conversion to increase
478 favorable habitats for biodiversity. The policies studied included taxes and/or subsidies for different
479 agricultural activities, such as, changes of the Common Agricultural Policy in the European Union
480 (Mouysset et al., 2012). In these studies, the state of biodiversity is assessed with habitat suitability
481 approaches in which the crops’ suitability for species of interest is assessed and these species serve as
482 proxy of the overall state of biodiversity. For instance, Chiron et al (2013) uses an index of specialization
483 of bird to either arable or grassland habitat.

484 **Group 5 (n=5).** This group was smaller than the other groups and predominantly used a “participatory”
485 approach, with stakeholders in several workshops. The agricultural landscape is represented as the
486 interplay between the land manager’s behavior, vegetation change, and other biological processes such
487 as carbon sequestration. The demand for different sectors for resources drives the amount of land use
488 and their allocation within the region. Mechanistic models are used in 4 out of 5 studies to represent
489 and simulate the evolution of landscape in scenarios. Such model is a chain of process-based models
490 that targets different parts of the modelled landscape. These included a series of “prototype models”
491 (Drum et al., 2015), input-output models coupled to resource flux model (Walz et al., 2007), models of
492 socioeconomic and biophysical processes (Reed et al., 2013), and agricultural landscape change models
493 (Berger and Bolte, 2004). Scenarios were predominantly complex storylines built during several
494 workshops with a large range of stakeholders, encompassing for instance local governments, local

495 agencies related to agriculture or other sectors, and, general public. Stakeholders usually share their
496 vision of local development, such as, opportunities and threats of the agricultural landscapes. During
497 these workshops, a shared representation of the system under study was developed, and storylines
498 were then drawn based on how the region could develop in the future.

499 **Group 6 (n=11).** This group comprised studies that were large-scale, with eight out of 11 ">1000 km²"
500 (median = 10,000 km²). The agricultural landscape is represented as the result of the decisions of
501 multiple landowners in terms of land use governed by their resources and preferences for given land
502 categories in "Optimization models". The utility of the landowner is maximized to produce scenarios in
503 which "multiple drivers" are accounted for and targeting multiple issues. The impact of "multiple
504 drivers", such as price change, change of demand, and climate change, are tested in "transformative
505 change" scenarios that are produced along with a storyline explaining the evolution of the system
506 modeled (Penker and Wytrzens, 2005). Once the model is run to produce the alternative agricultural
507 landscape, indicators are calculated on "Multi-issues". These issues are mainly the production of food
508 and fiber with aggregation of yields per area and also other services, along with biodiversity
509 conservation such as carbon sequestration or water provision and the trade-offs among these services
510 (Briner et al., 2013). In eight studies, "landscape indicators" are used for the assessment of biodiversity
511 change such as the proportion of natural vegetation land in part of a region (Bryan et al., 2011).

512 The multidimensional space contained two distinct clusters of groups: A cluster with groups 1, 2, and 3
513 and a cluster with groups 4, 5, and 6 (Figure 5). The description of groups 1, 2, and 3 tended to be
514 oriented towards the study of biodiversity, while the description of groups 4, 5, and 6 was more
515 oriented towards multi-issues.

516 3.3 The importance of issues targeted in approaches to biodiversity change in the landscape

517 <Insert Figure 6>

518 The regression tree split the population of studies into five leaves (A-E) using three variables: "issues",
519 "model to design landscapes" and "species behavior" (Figure 6). CART gathered all studies from group 6
520 into leaf E because they all targeted many different issues (level "multi-issues" within variable "issues").
521 Most studies from the group 4 (11 out of 14) were gathered in leaf D. They corresponded to studies
522 combining "no model" for design, and targeting "biodiversity coupled to one or two other issues". Leaf B
523 gathered 10 out of 14 studies of group 2 and leaf A encompassed 13 out of 14 studies of group 3. No
524 specific leaf captured the studies from group 5, which were spread between leaves A, B, and E. This can
525 be explained by the low number of studies (n=5) and by the few specificities of the studies in this group.
526 In fact, only three salient variables emerged in the group description for this group, while there were 5-6
527 salient variables for the other groups (Table 3). Despite the absence of group 5, the overall quality of the
528 regression tree was good, with 52 studies out of 67 well-classified (78%). The regression tree revealed
529 that "issues" was a main variable discriminating the different studies in the dataset (Figure 6). The
530 variable "issues" actually appeared twice in the regression tree, as a first-level and third-level node. The
531 studies were then discriminated based on whether they used/did not use a model to design the
532 agricultural landscape. The left part of the regression tree was discriminated based on whether or not
533 the behavior of species was accounted for in studies. The tree showed that the number of issues
534 targeted initially drives the type of approaches to study biodiversity change in landscape. Assessment of
535 many trade-offs, in terms of delivery of services, drives scientists towards "large scale multicriteria
536 studies of innovative scenarios combined with optimization". It also showed that using a model to
537 modify landscapes explains the type of approaches to study biodiversity change and that generally,
538 when models are used to explore landscape, the same models are re-used to assess the level of
539 biodiversity. This is the case for the group 1 "Biodiversity based agent based models" and 4

540 “Bioeconomic modelling of policy impacts in favor of restoration of beneficial habitats” that use
541 respectively agent-based and optimization models, coupled to indicators to produce landscape and
542 assess their response to biodiversity.

543 **4. Discussion**

544 Based on the diversity of the approaches highlighted, we discuss the advantages and disadvantages, the
545 objectives and type of data used, which can explain the choice of the method. Then, we make some
546 suggestions for methodological improvement in terms of potential combination of methods and
547 characteristics among groups for a better use of scenario analysis in regards to biodiversity
548 conservation. Our suggestions comprise: 1) Increasing the precision of biodiversity modelling in multi-
549 issues studies by combining approaches from groups 1 and 3 with groups 4 and 6; 2) coupling empirical
550 studies of taxa to broad biodiversity modelling to integrate the use of species’ behavior in groups 1 and
551 2; 3) transferring the more transformative scenarios used in groups 5 and 6 to other groups; and 4)
552 combining the methodologies of groups 3 and 4 to better account for agricultural activities and
553 landscape organization as a driver of biodiversity.

554 4.1 Advantages and disadvantages of approaches in linked with their objective and data use

555 Firstly, we argue that the approaches highlighted by the typology do not have the same objectives and
556 present advantages and disadvantages regarding the challenge of improving biodiversity conservation in
557 agricultural landscapes. Group 2 “Expert-based exploration of land use change with GIS” and group 3
558 “Land use approaches of biodiversity with spatially explicit statistical model” can be considered as
559 disciplinary ecological studies that aim to observe the population dynamics change in scenarios with
560 precise biodiversity data available on the area of interest and covering a large time frame. They tend to
561 focus on a single species in relation to some requirements, such as nesting or foraging for group 2, and
562 in relation with landscape complexity in group 3. Their disadvantages include the limited range of issues
563 targeted, and especially the lack of trade-offs among biodiversity conservation as well as other issues of
564 interest in landscape planning, such as production, economic profit, or nitrogen cycling. In Group 1
565 “Biodiversity-based agent-based models”, the focus of the study moves to a decision-making
566 perspective with the use of ABM simulating a landowner’s decision and the trade-off between
567 biodiversity conservation and production or economic profitability. The landowner decision is simulated,
568 along with a precise assessment of biodiversity change in the landscape, with the use of species’
569 behavior. In this group, the focus is still biodiversity, and the effect of landowner’s management on it,
570 with limitations in addressing other landowners’ or stakeholders’ concerns. The other approaches
571 expanded the scope of the assessment to multiple issues linked to the sustainability of agricultural
572 landscapes. Group 4 “Bioeconomic modelling of policy impacts in favor of the restoration of beneficial
573 habitats” and group 6 “Large-scale multicriteria studies of innovative scenarios combined with
574 optimization” present approaches that target policy making. Their main difference is the spatial extent,
575 larger in group 6, which prevents the use of habitat suitability approaches. In these two groups, policy
576 recommendations are made on a large range of issues, but the assessment of biodiversity is more
577 uncertain due to the use of simplified approaches of habitat modeling and landscape indicators. These
578 also hamper the understanding of scenario consequences on species temporal dynamics. Finally, group
579 5 is more oriented towards long-term decision-making aid by co-building scenarios to strengthen
580 decision making regarding the future of agricultural landscapes.

581 The accuracy with which the dynamic of biodiversity is assessed in agricultural landscapes is greater in
582 groups 1,2 and 3, than in groups 4, 5 and 6. It is not only related to the objective of approaches, but also
583 to the data used. Local to regional studies will most often provide specific complete measurements of
584 richness and abundance with small time steps. This captures precise population dynamics in relation to

585 landscape characteristics (Chiarucci et al., 2011). These time steps allow the use of mechanistic or agent
586 based models of evolution of biodiversity. For instance, the skylark population model used in Guillem et
587 al., (2015) is based on multiple continuous observations, which allowed the simulation of population
588 change on a daily basis. On the contrary, larger spatial analyses will primarily use species-area
589 relationships (e.g., Kreft et al., 2008) (as we observed in group 4, 5 and 6) which require less accurate
590 data in a larger extent and is less constraining in terms of time step with less regular measurements. The
591 need for precise data on a broad scale hampers the development of mechanistic or agent based models,
592 and, scientists therefore need to rely on metrics to assess biodiversity, such as the share of extensively
593 cultivated meadows (Briner et al., 2013). Indeed, large sampling with small time steps are logistically
594 very complicated (Palmer et al., 2002). Therefore, large-scale studies rely on metrics developed in the
595 literature, or on limited data to address the complex processes of biodiversity.

596 Improving biodiversity conservation in agricultural landscapes requires more precise assessment of the
597 population dynamic of multiple taxa as well as other issues linked with the landowner's decision and
598 other stakeholders that participate in the management of agricultural landscapes. Combining
599 approaches from disciplinary studies at small scale, understanding species dynamics and its links with
600 landscape complexity, with approaches at a broader spatial scale, using landscape indicators or proxies
601 studied on several species and integrating socio-economic issues and other environmental aspects,
602 could improve biodiversity conservation in agricultural landscapes.

603 4.2. Increasing the precision of biodiversity modelling in multi-issue studies

604 The choice of issues targeted by scientists appeared to be a major variable driving the characteristics of
605 approaches. The number of issues and the type of model used were strongly linked. With an increase in
606 the number of issues targeted in studies, the type of model tended to switch from complex types,
607 namely agent-based models and mechanistic models, to more simple habitat models or landscape
608 indicators that do not integrate species behavior or spatially explicit landscape processes. More complex
609 tools, at large scale, could provide a better assessment of the impacts of landscape change on
610 biodiversity, accounting for more drivers of abundance change, which are simplified in groups 4 and 6.
611 In these groups, optimization models were used to design landscapes, but this type of model is only
612 partially spatially explicit (Delmotte et al., 2013) and cannot embrace the full range of spatially explicit
613 drivers and species behavior in biodiversity-based landscape studies. Mechanistic and agent-based
614 models are more appropriate tools because they can account for processes such as behavior,
615 evolutionary and physico-chemical principles that drive the survival and reproduction success of species
616 (Grimm et al., 2017), and also socio-economic aspects of landscape design such as farmers' behavior
617 (Kremmydas et al., 2018). Group 1 "biodiversity-based agent-based models" is a type of approach that
618 models biodiversity change in such a way. This group only focused on biodiversity, although agent-based
619 models were frequently used in policy analysis to improve the sustainability of agricultural landscapes.
620 In these approaches, biodiversity was not included (e.g., Valbuena et al., 2010; Delmotte et al., 2013)
621 and changes in farmers' cropping plans were addressed rather than the consequences of such changes
622 on local or global issues. This supports findings in a recent review of agent-based model application in
623 agriculture by Kremmydas et al., (2018), where two studies out of 32 included biodiversity (Brady et al.,
624 2012; Guillem et al., 2015) (these two studies were also included in our review). Combining the
625 approach of group 1 using agent-based models with findings on species dynamics from approaches from
626 group 3, would help to integrate the influence of landscape complexity on population dynamic in agent-
627 based scenario studies. More interdisciplinarity in the development of agent-based models with
628 landscape indicators developed in approaches from the group 6 to assess economic, social and
629 environmental processes, could allow assessing trade-offs among biodiversity conservation as well as a
630 range of issues of interest for agricultural landscape planning.

631 4.3. Coupling empirical studies of taxa to broad biodiversity modelling

632 As our correlation table shows, the behavior of species was seldom accounted for when studies targeted
633 several taxa. Studies focusing on one taxon were very specialized but, when the number of taxa was
634 increased, the processes driving species population were simplified. Typically, in group 2 studies
635 (“expert-based exploration of land use change with GIS”), biodiversity change was integrated with
636 species behavior but the focus was on only one taxon. No study in our dataset approached a broad
637 range of taxa using a mechanistic model or agent-based model that integrated the behavior of species.
638 This reduced number of taxa in the assessment could be limiting in addressing the health of
639 agroecosystems, considering that different taxa respond differently to biotic and abiotic changes.
640 Although some species are indicators that represent the general health of a landscape in terms of
641 biodiversity, we stress the need for accounting for more indicator species. For example, some studies
642 aimed at finding species indicators of agricultural landscapes to represent the overall species richness of
643 other taxa have not been successful (Billeter et al., 2007). This is particularly true in a changing context
644 where global drivers such as climate change modify the state of agricultural landscapes to conditions
645 that could have unknown consequences on species. In these new states, indicator species may react
646 differently than other species. Large biodiversity studies should focus on species with different traits, to
647 monitor the change in the landscape and the trend in biodiversity richness. Typologies of species or
648 individuals based on traits could allow studies such as that by Hoffmann et al., (2016), which split the
649 population of skylarks into individuals i) with territorial behavior, ii) only resting and feeding guests, and
650 iii) overflying individuals without specific territories.

651 The low number of taxa included in the studies we reviewed is probably due to (1) low availability of
652 data on numerous taxa on a large spatial and temporal extent, which does not allow its use in agent-
653 based models, and (2) lack of information regarding the impacts of some changes in parameters on the
654 population trends of some taxa. This calls for i) better systematization of data collection on populations
655 of a large spectrum of taxa, and ii) more disciplinary studies on parameters driving species change of
656 taxa abundance across agricultural landscapes. According to Wetzal et al., (2018), there is a need to
657 unlock biodiversity data and form large-scale networks for systematic data collection, to help
658 understand species location and drivers and integrate these data in models and scenario studies.
659 Moreover, prediction of biodiversity change would improve future disciplinary studies addressing
660 various drivers of population related to landscape characteristics, e.g., habitat requirements (Steen et
661 al., 2012), predation (Luo et al., 2018), and biotic parameters (temperature, light, etc.). Grimm et al.,
662 (2017) call for the development of “re-usable sub models to represent behaviors and mechanisms such
663 as growth, uptake of nutrients, foraging, that could be applied to large areas of study. Typically, this type
664 of model is used in group 2 and 3 and focuses on the species’ behavior and landscape complexity impact
665 on biodiversity conservation. We believe that a generic model of species populations could be built and
666 calibrated following the same type of structure as crop models developed for modeling crop growth that
667 encompass large numbers of species, from annual to perennial, growing under different climate
668 conditions (Brisson et al., 2003; Jones et al., 2003; Keating et al., 2003). Ecological studies at small scale
669 could provide information on key processes related to species’ behavior, such as reproductive rate and
670 nesting conditions, as well as landscape complexity. This production of knowledge on several taxa could
671 be combined with the search and application of landscape indicators that could be used on larger scales
672 such as the approaches in group 6.

673 4.4. Participatory process to develop more transformative scenarios

674 Solving complex and dynamic environmental problems requires flexible, transparent decision-making
675 and innovative solutions (Reed 2008). Such solutions are embodied in complex “system” or

676 “transformative” scenarios. In the studies reviewed here, this type of scenario was more frequently
677 developed in a participatory process. This is due to the amount of knowledge needed in order to
678 describe how a set of drivers may change in time following several directions, and the impacts of local
679 agricultural systems. The choice of model to represent the landscape seems to guide the type of
680 scenario that can be built. To develop complex scenarios, models should be able to represent several
681 inputs of landscape that can be manipulated by the modeler. Statistical models seem inappropriate,
682 because the processes behind land use change are not clearly described, but based on regression
683 coefficients describing the probability of change from one land use to another. Hence, this type of
684 model is rarely used in participatory processes, as mentioned by Verburg et al., (2006), who showed that
685 stakeholders question the results of such models. For optimization models, the literature shows the
686 same problem, with some difficulties for stakeholders in understanding the functioning of the model
687 and being able to modify the model to produce scenario impacts (Sterk et al., 2007). However, this issue
688 could be overcome with iterative modelling steps and indicator contextualization with stakeholders
689 (Delmotte et al., 2017). In agent-based models, stakeholder participation often occurs and they may
690 even contribute to building the model, using it, and assessing scenarios, as in the companion modelling
691 approach (Antona et al., 2005; Hossard et al., 2013). In group 5 “participatory simulation studies of
692 landscape futures”, stakeholders are typically involved in the choice of models, the scenario definition,
693 and the assessment process. They are not simply consulted or asked to provide expertise. In the study
694 by Drum et al., (2015) for instance, stakeholders worked in several workshops to develop a conceptual
695 framework that describes the complex components of landscape and biodiversity change. This
696 participatory process allows for more exchange on the functioning of the system and on concepts across
697 disciplines. The inputs of stakeholder participation in scenario analysis have been recognized as an
698 important contribution to build knowledge and implement actions. Landis (2017) states that “Designing
699 agricultural landscapes will require that scientists work with stakeholders to determine the mix of
700 desired ecosystem services, evaluate current landscape structure in light of those goals, and implement
701 targeted modifications to achieve them”. The future of biodiversity depends on actions taken today by a
702 variety of stakeholders to overcome the complexity that creates its conservation (Couix and Hazard,
703 2013). More participatory scenario generation and collective visioning are urgently required to enable
704 policy developments and broad societal consensus on biodiversity conservation based on sound science
705 (Hill et al., 2013).

706 4.5. Merging agronomy and ecology into landscape science

707 Integrating stakeholders is a necessary condition in the development of complex scenarios, but
708 improving the biodiversity abundance and the sustainability of agricultural landscapes will also require
709 more integrated studies with various disciplines and scientists, especially agronomists and ecologists. In
710 this review, we found that the distinct group 3 studies on “land use approaches of biodiversity with
711 spatially explicit statistical model” and group 4 studies on “bioeconomic modeling of policy impacts in
712 favor of restoration of beneficial habitats” used different representations of the landscape, with a land
713 cover description for group 3 and a crop perspective for group 4. Both types also used different model
714 types, with group 3 using statistical models very typical of ecologists and group 4 using bioeconomic
715 model that are typical of agronomists/agro-economists. These two groups thus display a disciplinary
716 difference in model use. Both types of approaches could be combined to better account for the diversity
717 of cropping systems, species behavior and landscape complexity. The combination would allow
718 disaggregating land uses in regression models and accounting for the area covered by the different
719 cropping systems, rather than only land cover. Using a typology of farming or cropping system at
720 landscape level could benefit the analysis, by grouping cropping systems based on traits affecting
721 biodiversity population (soil disturbance, pesticide use). Moreover, for each type of cropping system,
722 the habitat value could be measured or estimated based on the characteristics of the system (Puig-

723 Montserrat et al., 2017). On the other hand, studies of agricultural system change impact on biodiversity
724 are seldom addressed with statistical models describing the spatial configuration of agricultural
725 landscapes. There is a general lack of landscape variables addressing the configuration of landscape, the
726 aggregation of crops, or the connectivity of habitats. In addition, we noted that optimization models
727 were usually used for optimization of farmers' revenue, while maximization of biodiversity abundance
728 could provide some interesting solutions to solve the biodiversity issue. This disciplinary difference has
729 already been noted by some authors, e.g., Benoît et al., (2012) call for landscape agronomy that is the
730 "interdisciplinary integration of farming systems in wider landscape research". Agronomy to date has
731 predominantly focused on field performance, with a lower interest in interactions between farming
732 practices and landscape processes through which biodiversity change occurs. When addressing
733 landscape dynamics, scientists should focus on the interactions between landscape organization, natural
734 resources like biodiversity status, and farming practices applied at field level.

735

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739

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1073 **List of Figures and Tables**

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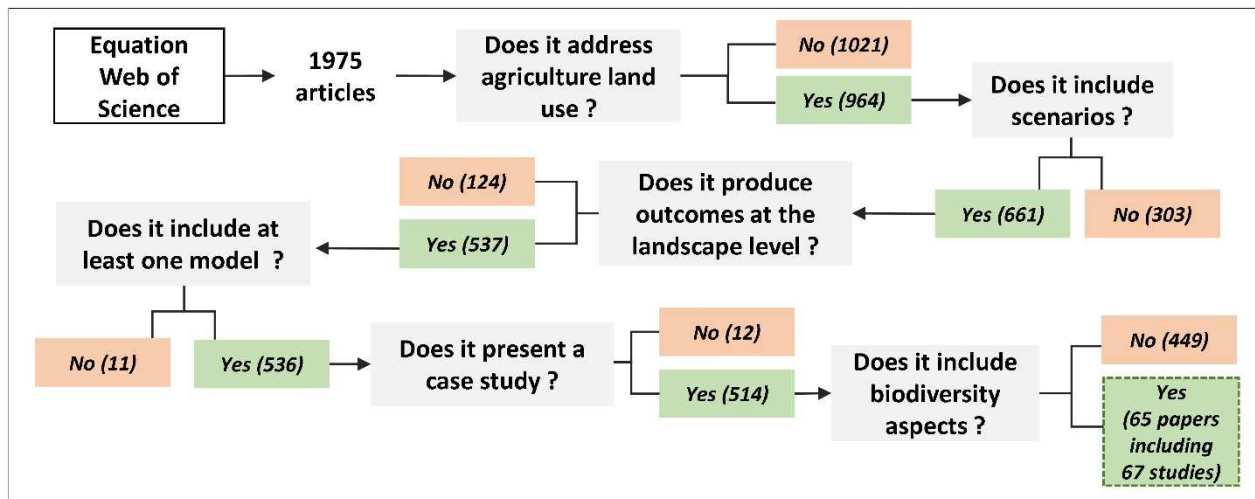


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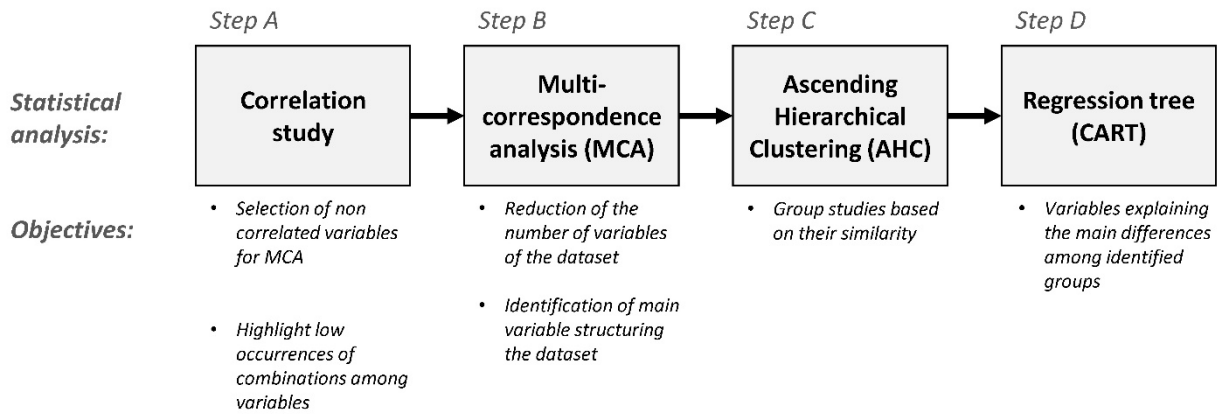


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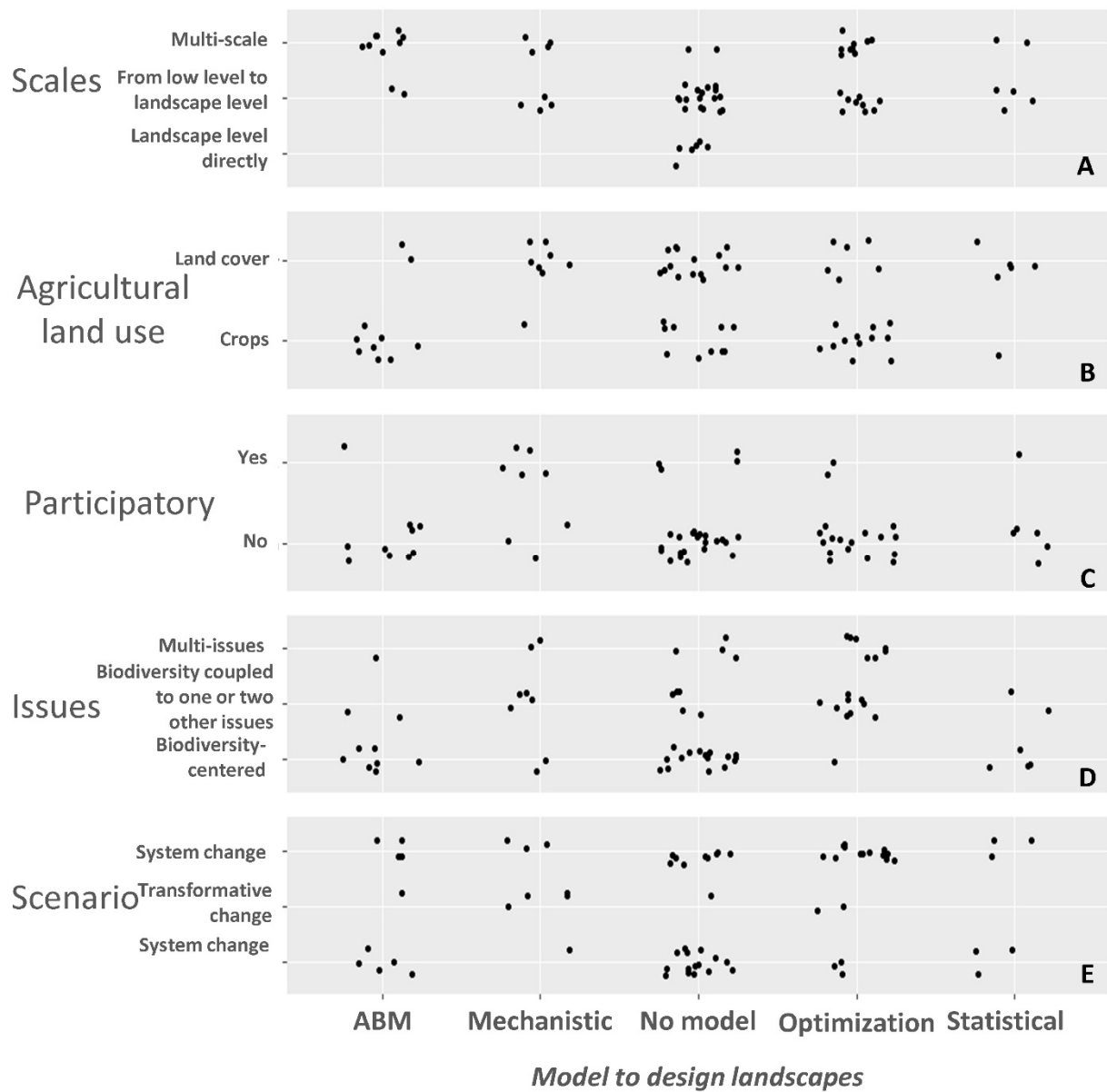


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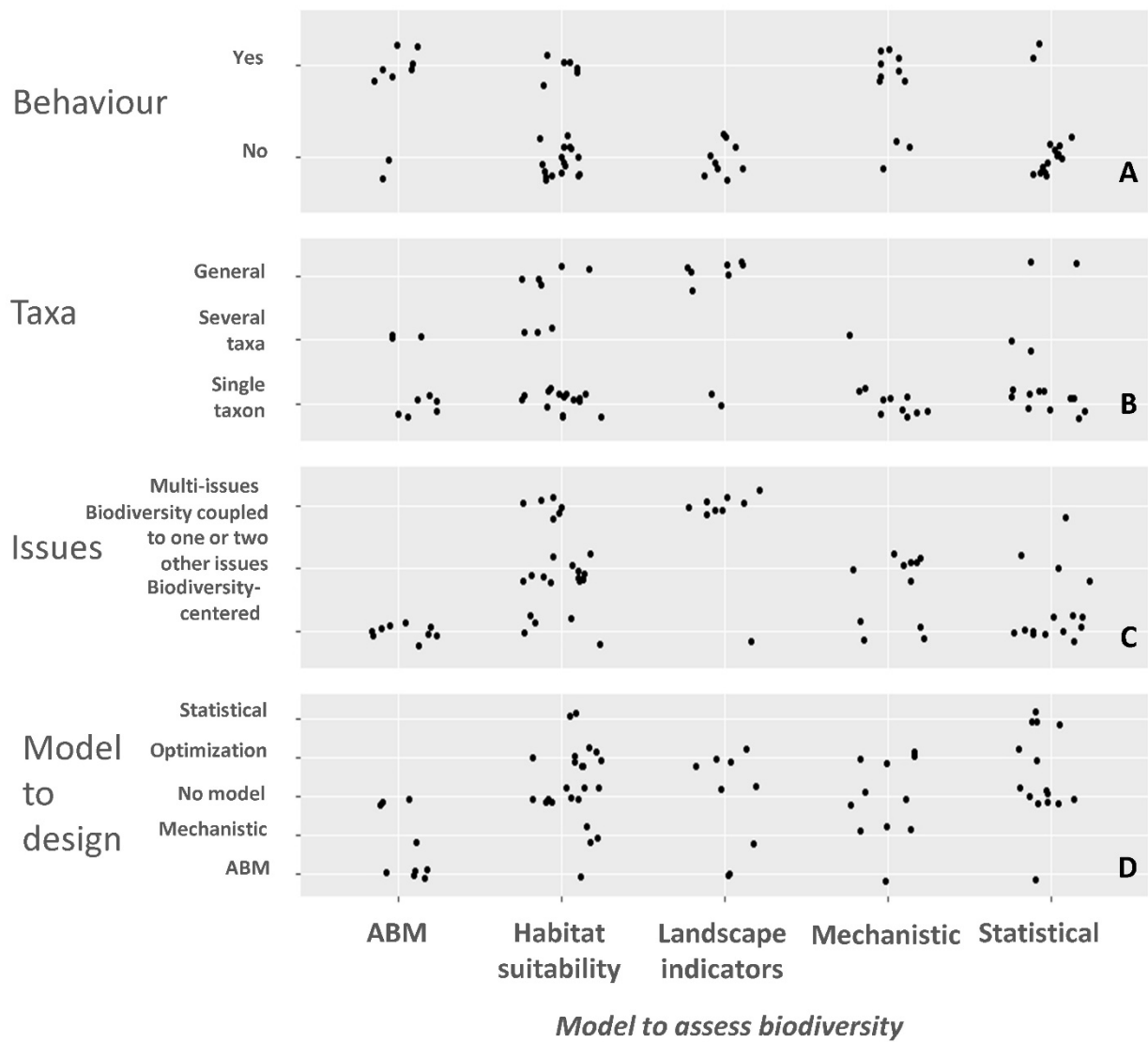


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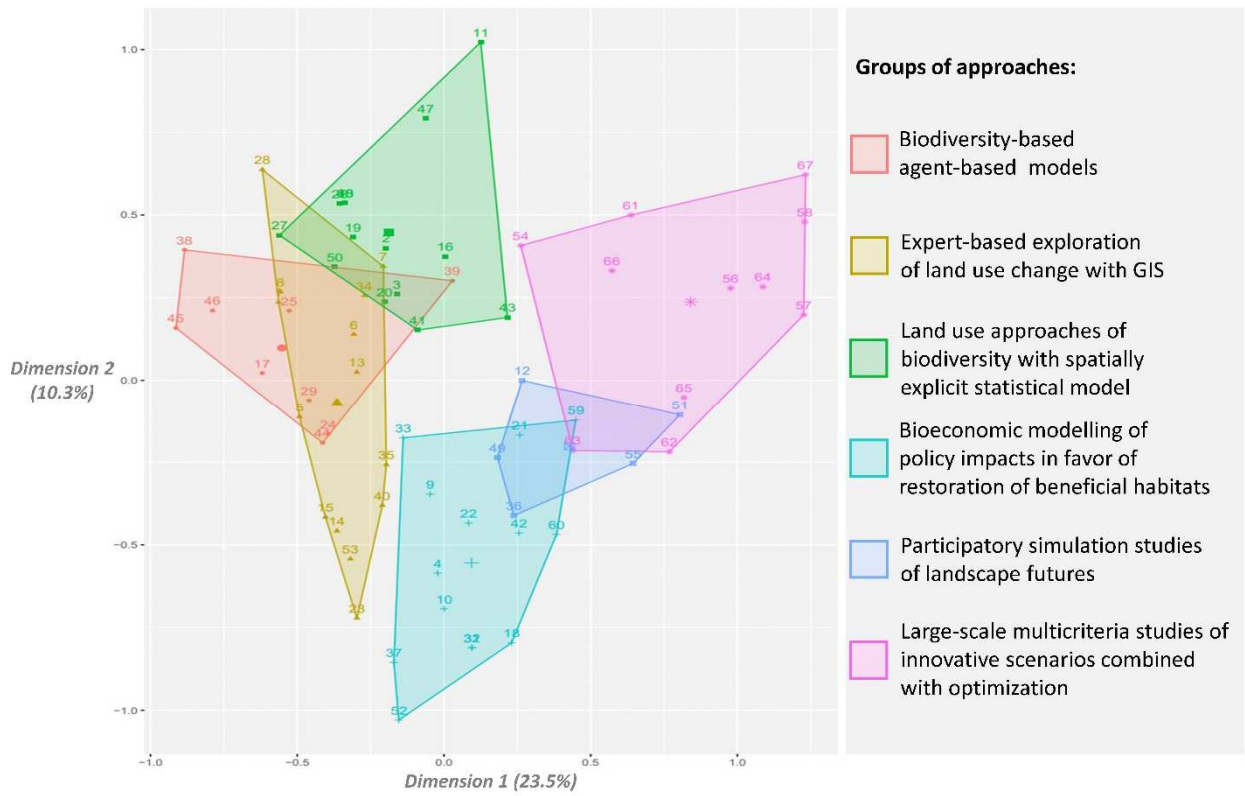


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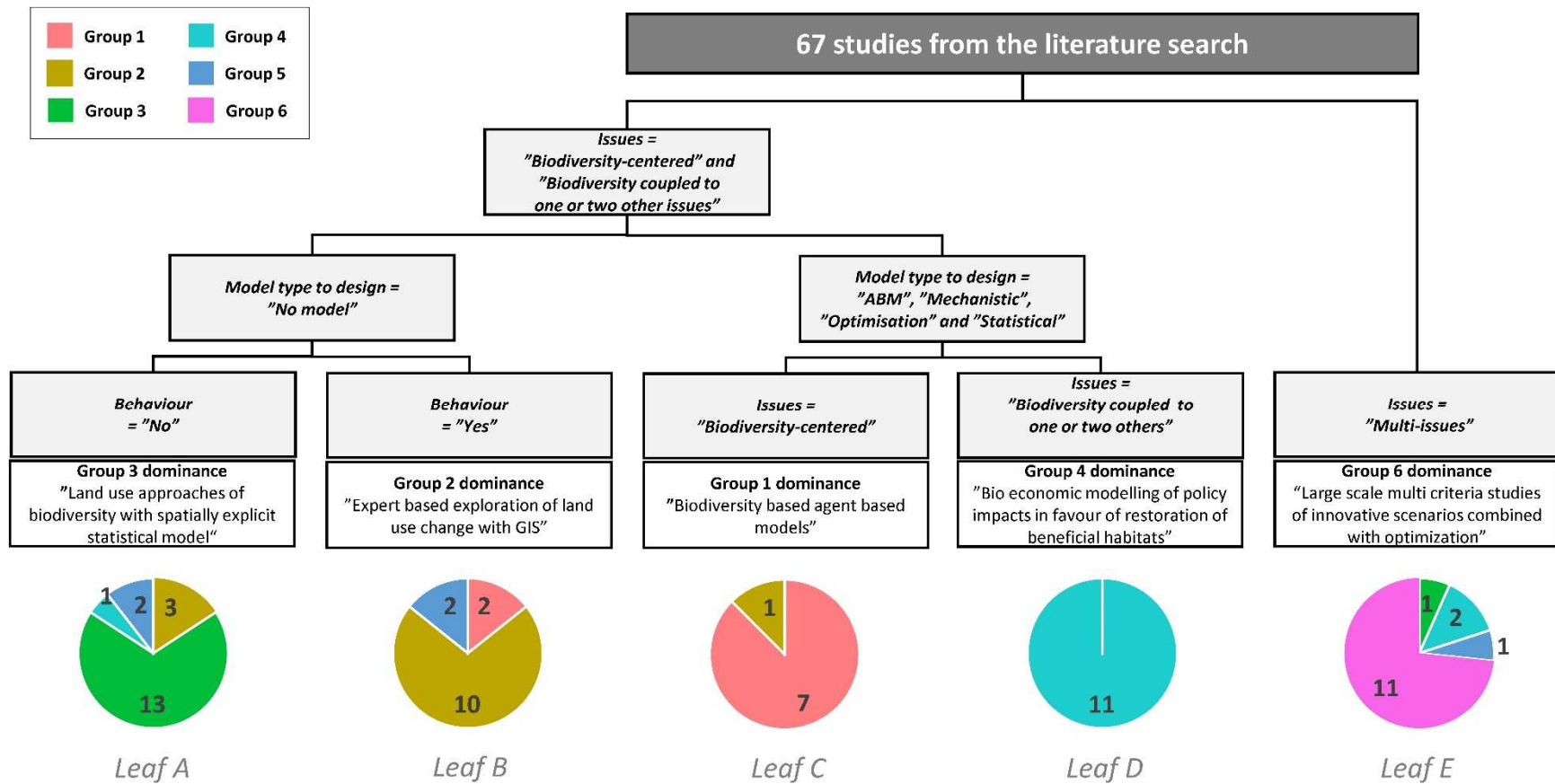


Figure 6: Regression tree showing the variables best explaining the classification of studies obtained with ascending hierarchical clustering (AHC). Thresholds for categorizing studies are enclosed in light grey boxes and the different groups of studies identified by the regression tree are given in white boxes. The pie charts represent the proportion of each group from the AHC included in each group obtained with the regression tree represented as leaves (A-E).

Table 1: The five variable categories, variable name, abbreviation, type, and sub-categories, and frequency of occurrence (n) in the selected papers

Category	Qualitative variable	Abbreviations	Ordinal/ Nominal	Subcategories	n
Spatial characteristics	Extent	<i>Extent</i>	Ordinal	<= 100 km ²	17
				100-1000 km ²	24
				>1000 km ²	26
	Spatial scales	<i>Scales</i>	Ordinal	Landscape level only	6
				From low level to landscape level directly	36
				Multi-scale (at least three scales)	25
Landscape description	Agricultural land use precision	<i>Agricultural land use</i>	Nominal	Land cover	35
				Crops	32
	Type of change of land use	<i>Landscape change</i>	Nominal	Change of activity	33
				Change of intensity	7
Biodiversity	Spatially explicit process driving biodiversity change	<i>Landscape system factor</i>	Nominal	Yes	26
				No	41
	Species behavior	<i>Behavior</i>	Nominal	Yes	23
				No	44
	Number of taxa	<i>Taxa</i>	Ordinal	Single taxon	44
				Set of taxa	9
General biodiversity				14	
Scenario	Participatory	<i>Participatory</i>	Nominal	Yes	13
				No	54
	Issues addressed	<i>Issues</i>	Ordinal	Biodiversity coupled to one or two other issues	22
				Multi-issues	15
				Biodiversity-centered	30
	Drivers of landscape change	<i>Drivers</i>	Nominal	Single driver	54
				Multiple drivers	13
	Scenario types	<i>Scenario</i>	Nominal	Simple change	27
System change				32	
Transformative change				8	
Modeling	Model to design landscapes	<i>Model to design</i>	Nominal	Agent-based model	10
				Mechanistic model	8
				Optimization model	18
				No model to design	25
				Statistical model	6
	Model to assess biodiversity	<i>Model to assess</i>	Nominal	Agent-based model	9
				Mechanist model	11
				Habitat suitability	23
				Landscape indicators	9
				Statistical model	15

Table 2: Correlations among the 13 variables. Chi-square tests were performed to test the significance of correlation among nominal variables and between nominal and ordinal variables. Strength of the correlation was assessed using Cramer's test value, with a value between 0.2-0.4 indicating a slight correlation, 0.4-0.6 indicating a moderate correlation and a value above 0.6 a strong correlation. Correlations among the ordinal variables were tested using the Goodman-Kruskal gamma test, with values ranging between 0 (no correlation) and 1 (perfect positive correlation)

		Extent	Scales	Agricultural land use	Landscape change	Landscape factor	Behavior	Taxa	Participatory	Issues	Drivers	Scenario	Model to design	Model to assess
		Ordinal	Ordinal	Nominal	Nominal	Nominal	Nominal	Ordinal	Nominal	Ordinal	Nominal	Nominal	Nominal	Nominal
Extent	Ordinal	-	-	-	-	-	X ² = 11.08 pval<0.01*** Cramer= 0.41	-	-	X ² = 16.87 Pval<0.01*** Gamma= 0.36	-	-	-	-
Scales	Ordinal		-	X ² = 7.57 Pval =0.02** Cramer= 0.34	-	-	-	-	-	-	-	-	X ² = 25.19 Pval<0.01*** Cramer= 0.43	-
Agricultural land use	Nominal			-	-	-	-	-	-	-	-	-	X ² = 13.66 Pval<0.01*** Cramer= 0.45	-
Landscape change	Nominal				-	-	-	-	-	-	-	-	-	-
Landscape factor	Nominal					-	-	-	X ² = 7.36 Pval<0.025** Cramer= 0.33	-	-	-	-	-
Behavior	Nominal						X ² = 14.26 Pval<0.01*** Cramer= 0.33	-	-	X ² = 6.59 Pval=0.04** Cramer= 0.31	-	-	-	X ² = 23.06 pval<0.01*** Cramer= 0.59
Taxa	Ordinal							-	-	-	X ² = 7.43 Pval<0.02** Cramer= 0.33	-	-	X ² = 26.34 Pval<0.001* Cramer= 0.59
Participatory	Nominal								-	-	-	X ² = 20.08 p-val<0.01*** Cramer= 0.55	X ² = 11.07 Pval=0.02** Cramer= 0.41	-
Issues	Ordinal									X ² = 10.38 Pval<0.01*** Cramer= 0.39	-	-	X ² = 21.52 Pval<0.01*** Cramer= 0.40	X ² = 50.55 Pval<0.01*** Cramer= 0.61
Drivers	Nominal										X ² = 13.88 p-val<0.01*** Cramer= 0.46	-	-	-
Scenario	Nominal											-	X ² = 21.88 pval<0.01*** Cramer= 0.40	-
Model to design	Nominal													X ² = 32.10 pval<0.01*** Cramer= 0.35

Table 3: Description of the six groups of approaches and the most frequent category of each variable when one was overrepresented. Overrepresentation was tested with V-test. A value between 2 and 3 denotes slight overrepresentation of the factor value in the group (*), a value between 3 and 5 denotes moderate overrepresentation (**) and a value above 5 represents important overrepresentation (***) (Husson et al. 2015). No overrepresentation is indicated with “-”

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Name given to the group	Biodiversity-based agent-based models	Expert-based exploration of land use change with GIS	Land use approaches of biodiversity with spatially explicit statistical model	Bioeconomic modelling of policy impacts in favor of restoration of beneficial habitats	Participatory simulation studies of landscape futures	Large-scale multicriteria studies of innovative scenarios combined with optimization
Case study in the center of the group	Study 45 Topping et al. 2015	Study 15 Everaars et al. 2014	Study 2 Benett et al. 2014	Study 9 Chiron et al. 2013	Study 12 Drum et al. 2015	Study 66 Kniess et al. 2016
Number of studies the group	9	14	14	14	5	11
Extent	-	-	-	-	-	>1000 km ² **
Spatial scales	Multi-scale*	From low level to landscape level directly*	-	-	-	-
Description of land use	-	-	Land cover **	Crops **	-	-
Type of change of land use	-	-	-	-	-	-
Spatially explicit process driving biodiversity change	-	-	Yes*	-	-	-
Species behavior	Yes *	Yes**	No*	-	-	-
Number of taxa	-	Single taxon **	-	-	-	General biodiversity**
Participatory	-	No*	-	-	Yes**	-
Issues addressed	Biodiversity centered **	-	Biodiversity centered **	Biodiversity coupled to other issues **	-	Multi-issues ***
Drivers of landscape change	-	-	-	Single driver *	-	Multiple drivers**
Scenario types	-	-	-	System change *	Transformative change**	Transformative change**
Model to design landscapes	Agent-based model **	No model to design **	Statistical model** No model to design**	Optimization model**	Mechanistic model **	Optimization model **
Model to assess biodiversity	Agent-based model **	-	Statistical model**	Habitat suitability**	-	Landscape indicators ***