Model-based integration of ecology and socio-economics for the management of biodiversity and ecosystem services: state of the art, diversity and current trends

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Abstract

Models are important tools to integrate ecological and socio-economic knowledge to better understand and manage social-ecological systems. Challenges include, among others, the adequate representation of feedback loops between the socio-economic and the ecological subsystems, uncertainties and human behaviour. To analyse how well models are able to address these challenges in the fields of biodiversity conservation and ecosystem services management the present paper systematically reviews recent mechanistic models of the field and analyses them with respect to a number of binary criteria. The reviewed models generally contain quite a few of the above-mentioned system features but still fall short when it comes to the adequate representation of the socio-economic dimension. Sorting the models by the labels given to them by their authors, such as "ecological-economic" or "system-dynamic", allows assessing model variation within and among labels and indicates that there is a fruitful level of diversity in the models.

Highlights

- Papers with models integrating ecological and socio-economic knowledge are reviewed
- Considered fields of application are biodiversity conservation and ecosystem services
- Models contain important features but generally miss important socio-economic issues
- There seems to be a fruitful level of diversity among the models in the field

Key words

agent-based models, bio-economic models, ecological-economic models, social-ecological models, system-dynamic models.

1 Introduction

Despite various political and scientific initiatives (MA (2005), CBD (2007), IPBES: Díaz et al. (2018), TEEB (2010)), the loss of biodiversity and the degradation of ecosystem services is still ongoing worldwide (EEA 2019). Next to climate change, one of the main drivers of these losses is human land use (MA 2005), which in turn is driven by the socio-economic conditions, such as agricultural policy (e.g., Lakner et al 2019), under which the land users operate.

To understand the human-induced decline of biodiversity and ecosystem services, both the ecological and the socio-economic dimensions have to be considered in an integrated manner (Shogren et al. (1999), TEEB (2010), Wätzold et al. (2006)). A challenge here is that the coupled ecological and socio-economic processes are usually

- dynamic, partly involving feedbacks, so that, e g., the ecological subsystem affects the socio-economic subsystem and vice versa (Polasky and Segerson 2009),
- spatially structured, so that, e.g., the distance between habitats affects the dispersal and the survival of a species (Hanski 1999), or the deforestation in the tropics leads to the fragmentation of rainforests (Taubert et al. 2018),
- subject to risk and uncertainty, since for instance the dynamics of species populations are often influenced by random factors (Beissinger et al. 2002), or systems may tip from one state to another where the location of the tipping point is fully or partly unknown (Bauch et al. (2016), and
- influenced by non-trivial behaviour of humans, where humans partly try to maximise their economic profits but in their decisions are also influenced by other motives (e.g., Bartkowski and Bartke 2018).

Mathematical models have become important tools for the improvement and support of the understanding, prediction and management of complex systems, such as the world's climate system (e.g., Neelin 2010) or the dynamics of animal diseases (e.g., Vicente et al. 2019), which also holds for those cases in which several scientific disciplines, in particular natural sciences and social sciences, need to be considered in an integrated manner (Voinov (2008), Clark (2010), Flichman et al. (2011), Schlüter et al. (2012), Drechsler (2020)).

Purposes of models are manifold (Baumgärtner et al. 2008), probably the most important being a better understanding of systems and observed phenomena (e.g., Getzin et al. 2006, Taubert et al. 2018), prediction of system dynamics (e.g., Bauch et al. 2016), and decision support (e.g., EFSA et al. 2017).

To increase their relevance for decision support, models should ideally consider that human land use is often influenced by agricultural, environmental and other policies (de Vries and Hanley 2016, Pe'er et al. 2017). A major obstacle to the development of policies is asymmetric information (Laffont and Mortimort 2002). Following the environmental-economics literature (e.g., Hanley et al. 2007), a case of asymmetric information is present when one actor has more information about some relevant facts than another (e.g., when landowners know their costs of carrying out a conservation measure, but a conservation agency that wishes to introduce a conservation policy does not).

The question arises, (Q1) to what extent current models used for the integration of ecology and socio-economics in the fields of biodiversity conservation and the management of ecosystem services, capture the above-mentioned issues of spatial, temporal and behavioural complexity and address the needs of deciders and policy makers.

To address this question, a quantitative analysis of research papers from the field is carried out, based on a systematic search from the past five years and focusing on mechanistic models. The papers are analysed with respect to a number of characteristics, including the purpose for which the models have been developed and analysed, structural features such as spatial structure or dynamics, issues of system complexity such as emergence, models of human behaviour, issues relevant in policy making, and the method by which the model is implemented and analysed.

With regard to agent-based models, a similar analysis has been carried out by Groeneveld et al. (2017) who focus on behaviour of land users, and Egli et al. (2019) who explore the consideration of resilience in agent-based models. However, while these two reviews address model features similar to those listed above, they consider different fields of model applications and, most importantly, consider only agent-based models.

Agent-based models, however, form only a limited subset of models integrating ecology and socio-economics in the fields of biodiversity conservation and the management of ecosystem services. Instead, next to agent-based, models in the field are known under very different labels, such as bio-economic or system-dynamic. Including these other labels on the one hand broadens the scope of the analysis and on the other hand raises additional research questions: (Q2) Do different labels reflect different model structures, possibly implying different abilities of the models to capture the features, and fulfil the purposes, described above? Further, how strongly are models of different labels are related to each other and do the different labels indicate the presence of separate modelling communities with only limited communication among each other? To address these questions, the reviewed models are sorted by the labels given to them, and the models found under each label are analysed separately and the results compared among the different labels.

The way models are built and labelled may change over time, and thus research question Q3 reads: What are the magnitudes and statistical significance of these changes? To address the three research questions Q1–Q3, relevant papers from the years 2015–2019 are identified and analysed as outlined above and described in detail below in the Methods. The Results section presents the outcomes of the analyses, and in the Discussion conclusions are drawn from these outcomes to formulate answers to the three research questions.

2 Methods

2.1 Data collection

The research context of the present analysis is mechanistic, or process-based, models that explicitly consider both the ecological and the socio-economic dimension of problems in the field of biodiversity, resource, and ecosystem services management. The basis of the quantitative literature review is thus a search with Scopus, performed in February 2020, for „TITLE-ABS-KEY

- ((model* W/10 (social* OR socio* OR economic*))
- AND (model* W/10 ecological*)
- AND (biodiversity OR resource OR (ecosystem W/5 service)))
- AND (EXCLUDE (SUBJAREA , "MEDI") OR EXCLUDE (SUBJAREA , "BIOC") OR EXCLUDE (SUBJAREA , "ARTS") OR EXCLUDE (SUBJAREA , "PSYC") OR EXCLUDE (SUBJAREA , "NURS") OR EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "NEUR") OR EXCLUDE (SUBJAREA , "IMMU") OR EXCLUDE (SUBJAREA , "MATE") OR EXCLUDE (SUBJAREA , "PHYS") OR EXCLUDE (SUBJAREA , "CHEM") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE (SUBJAREA , "PHAR") OR EXCLUDE (SUBJAREA , "VETE"))

This search string was chosen to detect modelling papers considering (i) social, economic, or socio-economic dimension, (ii) an ecological dimension, and (iii) addressing issues of biodiversity, resources or ecosystem services (note that in Scopus the command W/n requires that the two connected keywords must not more than n words apart from each other). And to avoid an explosion of work load, thematic fields most likely to be irrelevant in the context of biodiversity were excluded. In total 1082 papers were identified, from which 73, 66, 85, 86 and 101 papers fell into the years 2015, 2016, 2017, 2018 and 2019, which form the basis of the present analysis.

Next, all the 411 papers were subjected to a rigorous manual screening process to avoid mis-classification of papers due to malfunctioning search filters (cf. Zare et al. 2017) and ensure that the remaining papers fall into the above-defined context. About twenty papers dropped out because they were not accessible (e.g., because they appeared in a journal of minor range), or not written in English language, and/or where the model description was too superficial (because, e.g., the paper is an extended abstract for a conference) to allow for the below-described detailed characterisation of the model. Then, a considerable proportion of papers dropped out whose models are of a qualitative/conceptual or statistical nature. Statistical models were excluded because these models are by their nature largely independent of the research context: a linear regression analysis, e.g., simply correlates data and looks the same, regardless whether the data are from biological, social or astronomic observations (cf. Drechsler et al. 2007). Quite a few papers also dropped out, because other than suggested by their title, keywords or abstract (which were the targets of the Scopus search), they included only one of the two dimensions of ecology and socio-economics or even none of them. Lastly, models containing a mere aggregation of numbers into an index, such as ecological-footprint analysis or simple multi-criteria analysis (that did not include any further ecological and socio-economic modelling) were discarded.

2.2 Selection of model characteristics and labels

As a result, 122 papers (cf. Appendix A in the Supplementary Material) are retained which (or precisely, of course: the models in which) are characterised by the purpose for which the model was built, the structure of the model, particular issues addressed, and the formal implementation and analysis of the model. The selection of the criteria was influenced by Drechsler et al. (2007), Baumgärtner et al. (2008), Schlüter et al. (2012), Egli et al. (2019) and Drechsler (2020), and the criteria are chosen to explicitly address the issues raised in the Introduction:

Is the model

1. general?
2. specific?
3. built for positive analysis?
4. built for normative analysis?
5. used to improve the understanding of the modeled system or develop theory?
6. used to make predictions of the system dynamics?
7. used to include stakeholders and/or support management decisions?

Does the model explicitly consider

8. system dynamics?

9. spatial structure?
10. randomness/stochasticity?
11. feedback loops?
12. individual agents?
13. networks?

Regarding human actions, does the model address issues of

14. asymmetric information?
15. prediction and learning of actors?

and is based on a

16. utilitarian framework, in particular the human model of *homo oeconomicus*?
17. or employing alternative, “non-classical” models of human behaviour?

Does the model analysis address issues of

18. non-linearity, such as resilience or discontinuous transitions/tipping points?
19. emergence, in particular spatial pattern formation?
20. policy interventions on the system?

Is the model formulated through

21. (differential or difference) equations?
22. algorithms and rules?

and is it solved or analysed

23. analytically, or
24. numerically/via computer simulation?

And, how was the model labeled by its authors?

Similar to Drechsler (2020), a general model is understood as a model that is not applied to a specific (geographically localised) case but formulated in a general manner by quantities like economic cost, population growth rate, etc. If a model is analysed numerically, it is counted as general if a systematic sensitivity analysis is carried out to explore the general behaviour of the model. A specific model, in contrast, is applied and parametrised to a specific case without any sensitivity analysis. Positive analysis is understood (cf. Drechsler 2020) as exploring how the system looks like or will develop, while normative analysis is understood as addressing how a system should be (managed) to maximise certain objectives like cost-effectiveness or social welfare.

Characteristic 7 is meant to capture participatory modelling approaches (e.g., Voinov et al. 2018), which includes research were stakeholders are not only sources of information (like in a survey) but actively and significantly involved in the research. Characteristic 12 contains multi-agent systems (Gilbert 2007) but also game theoretical approaches (Tadelis 2013; often with only two agents), while networks (characteristic 13) can, e.g., be ecological (Pascual and Dunne 2005) or social networks (Bruggeman 2008).

Asymmetric information (characteristic 14) was explained in the Introduction. Characteristic 16 measures whether decisions are based on the maximisation of some utility function (as does, e.g. a welfare-maximising policy maker or the rational utility-maximising *homo oeconomicus*), while non-classical models (characteristic 17) may include altruism or inequity aversion in agents (e.g., Fehr and Schmidt 1999), satisficing behaviour (Simon 1979) or social interaction such as copying opinions or decisions of other agents (Weisbuch 2005). Or the decisions may be modeled by statistical models (with the rest of the model being mechanistic as explained above) fitted to observed decisions (Lewis and Plantinga 2007), so that a utility function is, or cannot be, derived explicitly.

Most models in the sample include some non-linear elements. However, such non-linearity in the model structure (e.g., logistic growth of an animal population) does not necessarily lead to non-trivial model dynamics that can address issues of resilience or tipping points. Similarly, resource management models may contain a feedback loop in their formulation but may be analysed only to identify a monotonic optimal harvesting trajectory. Non-linearity in the context of the present paper (characteristic 18) does not refer to such non-linearities in the model *formulation* but only to the question of whether issues of non-linearity like resilience are addressed explicitly in the model *analysis*.

Characteristic 20 addresses, e.g., agricultural policies or the establishment of nature reserves. Some models contain policies as an exogenous driver but do not explicitly analyse the effects of these policies: these models are not classified as considering policy intervention. The last question above addresses the observation that models used in the present context have quite different labels, such as bio-economic or system-dynamic.

2.3 Determination of the frequency distributions of the model characteristics (research question Q1)

Having analysed all 122 papers with regard to the 24 characteristics, the relative frequencies of the models falling into each of these 24 categories are counted. Regarding the authors' label, many models have been given only an unspecific label like "simulation model" or "coupled model", and are classified as "not-specified". Although the label "network model" is specific, it is not particularly relevant to the issue of ecological and socio-economic integration, and so "network models" are also classified as "not-specified". For the five labels with the highest numbers of models the frequencies of the 24 characteristics are counted in the same way as for the set of all 122 models.

2.4 Determination of relationships between model labels (question Q2)

The counts of the model characteristics in the different model labels are used to identify characteristics typical for each model label to obtain a first understanding of the differences and similarities between the model labels. This is followed by a quantitative assessment of the relationships between the five model labels. For this, the frequency distributions are considered as vectors and Pearson correlation coefficients between these vectors are calculated. As an indicator of overlap and communication between different modelling communities, for each model label the journals are identified in which models of that label are published and the journals are identified that contain a particular number of model labels.

2.5 Determination of trends in the consideration of model characteristics and model labels (question Q3)

Although five years of data is a rather short time frame to detect significant trends, two trend analyses are carried out using linear regression with time as the explaining variable. In the first analysis the explained variables are the frequencies of the model characteristics within the sample of all 122 models, while the second analysis considers the frequencies of the five model labels as explained variables.

3 Results

3.1 Distribution of the model characteristics (research question Q1)

The general distribution of the characteristics, based on all 122 models, is shown in Fig 1. About one third of the models is general while two thirds are specific (note that the sum of general and specific models is slightly above 100 %, since a few papers contain both a general and a specific analysis). Almost 80 % of the models were used for a positive analysis while about 30 % are normative (note that some papers contain both a positive and a normative analysis). About half of the models were analysed for system understanding and theory development, about two third were used for prediction, while only about five percent were developed and applied in a participatory approach.

Half of the models consider spatial structure, stochasticity and feedback loops; 80 % are dynamic, but less than one third consider agents and less than ten percent consider networks. Asymmetric information is considered only in less than five percent of all models, and the consideration of prediction and learning is only slightly more abundant. About half of all models include some sort of utilitarian approach of decision making, less than 20 % assume non-classical human behaviour, while in the rest of the models modes of decision making or human behaviour are irrelevant or not addressed. About one third of the models address issues of non-linearity, while only ten percent consider emergence. Effects of policy intervention were analysed in about 30 % of the models. Lastly, about one third of the models is equation-based while two thirds are algorithmic, and almost all models were analysed numerically or by computer simulation.

3.1 Distribution of the model characteristics for the dominant model labels (research question Q2)

As described in the Methods, an issue of interest is the label attached to the model by its author(s). In the sample of 122 papers, 24 models were labeled “socio-ecological” or “social-ecological” (SEM), 23 are “ecological-economic” (EEM), 14 “bio-economic” (BEM), 13 “agent-based” or “multi-agent” (ABM), and eight are “system-dynamic” (SDM). Five models have two labels like “agent-based social-ecological model” or “ecological-socio-economic model” and were sorted in both respective classes. In addition, the labels “land use model” and “multi-objective model” are observed three times each and two “game models” are in the sample. The labels “business model”, “carbon cycle model”, “disease-economic model”, “growth model” and “socio-hydrological” occur once each, and all other models are “not specified” as defined in the Methods.

For the five most frequent labels, Fig. 2 shows the characteristics distributions, analogous to Fig. 1. Frequencies between 0.25 and 0.75 (this choice is, if course, somewhat arbitrary) in a characteristic indicate that both, presences and absences are quite abundant, so that this characteristic is neither very typical nor very untypical for the considered model label. Larger frequencies ≥ 0.75, in contrast, indicate that the characteristic is typical for the model label while smaller frequencies ≤ 0.25 indicate that the characteristic is untypical. Table 1 summaries for each label the typical and the untypical characteristics.

By these definitions of “typical” and “untypical”, participatory approaches or decision support are untypical purposes for all model labels. Except for the EEM, all model labels are typically dynamic. Typically, there is no consideration of networks, asymmetric information or learning. With the exceptions of ABMs, consideration of emergence is untypical. And models of all labels are typically analysed numerically.

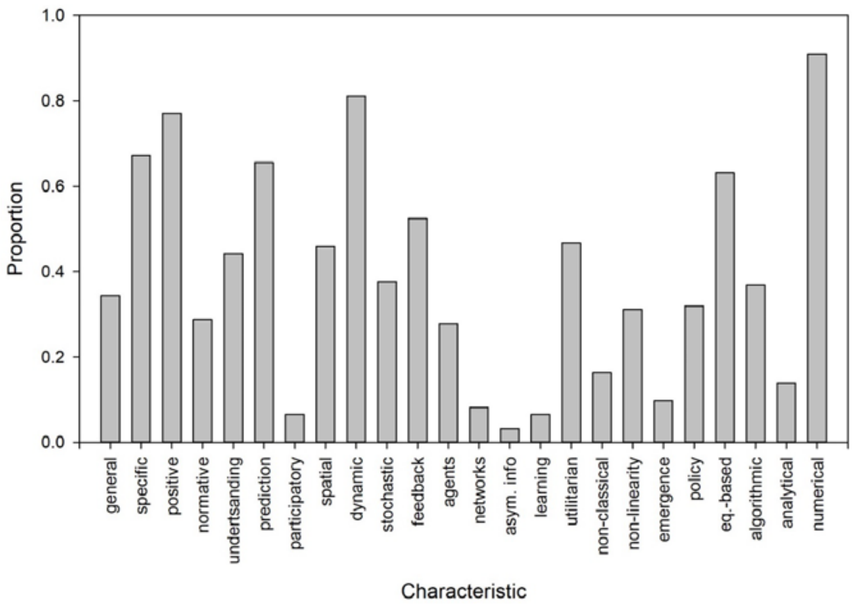

Figure 1: Relative frequencies of the model characteristics over all 122 model studies (for the numerical values, see Appendix B in the Supplementary Material).

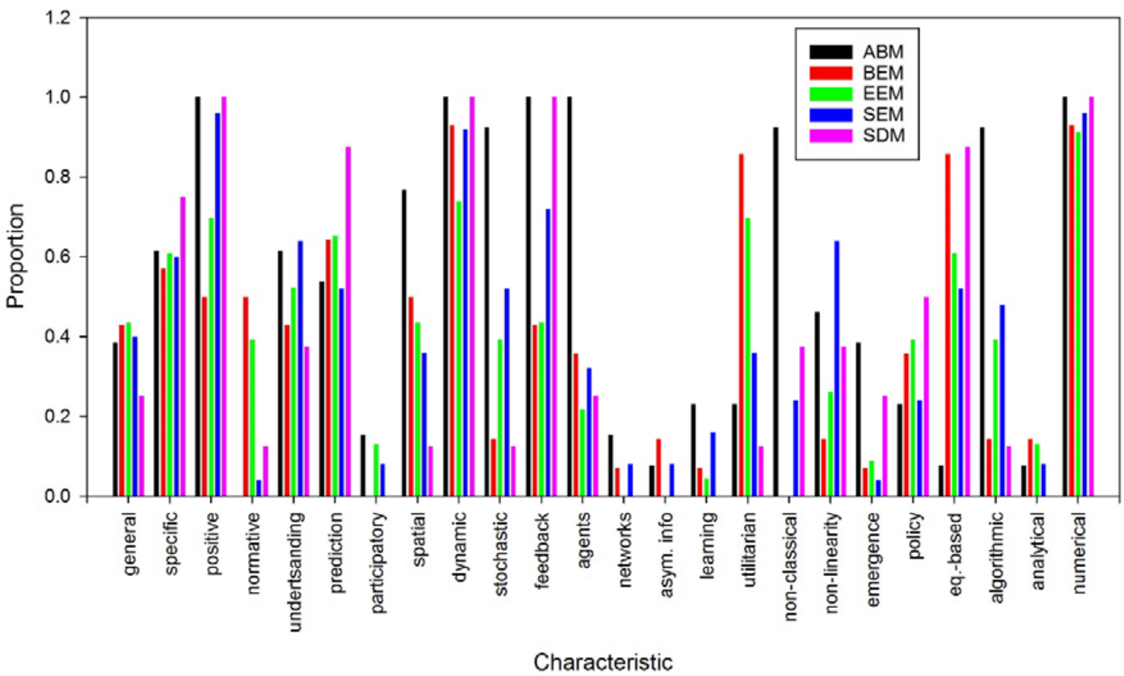

Figure 2: Relative frequencies of the model characteristics within the five most dominant model labels: agent-based models (ABM), bio-economic models (BEM), ecological-economic models (EEM), social-ecological models (SEM) and system-dynamic models (SDM) (for the numerical values, see Appendix B in the Supplementary Material).

Beyond this, ABMs (recall: according to the authors' own labelling) are typically used for positive and not for normative analysis, contain many of the features like stochasticity and feedbacks, etc., and consider non-classical human behaviour. Policy analysis is untypical, as well as an equation-based formulation. Instead the models are typically formulated (and solved) algorithmically.

BEMs are typically deterministic, employ a utilitarian framework like the human model of *homo oeconomicus* and are equation-based. They typically disregard non-linearities and are equation-based. Agent-based approaches, including the consideration of non-classical behaviour are untypical in EEMs. SEMs are very similar to the ABMs but in contrast – and like the EEMs – typically disregard non-classical behaviour and emergence.

SDMs are typically specific and not general, are used for positive rather than normative analysis and for prediction. They are typically non-spatial and deterministic but consider feedbacks. They do not consider agents, and since they are typically not used for normative analysis like cost-effectiveness analysis they also do not use a utilitarian framework. Like the BEMs they are typically equation-based.

If a model characteristic is found typical (or untypical) in only one model label then that model label may be regarded as distinctive in the considered characteristic (grey shaded cells in Table 1). By this definition, ABMs are distinctive by their consideration of spatial structure and stochasticity and, naturally, by their use of an agent-based approach. This allows them to distinctively consider non-classical behaviour and implies that they are formulated algorithmically rather than through mathematical equations. BEMs, in contrast, are distinctive by their use of a utilitarian framework and their formulation through equations. EEMs and SEMs are, by the present definition, not distinctive in any characteristic.

However, one should note that these outcomes, of course, depend on the choice of the thresholds (0.75 and 0.25) by which a characteristic is denoted as typical or untypical, respectively. The fact that SEMs, e.g., are not distinctive for feedback loops is because on the one hand the proportion of models with feedback loops in that label (0.72) is below the threshold of 0.75; and on the other hand, by the chosen definition, a model label is distinctive in a characteristic only if it is the *only* label in which that characteristic is typical. And because feedback loops are typical also for ABMs, if the threshold was lowered for instance to 0.7, feedback loops would be typical for both ABMs and SEMs – and none of both labels would be judged distinctive with respect to feedback loops. Therefore, if a label is not denoted as distinctive by a particular characteristic this does not imply that this characteristic is rare in that label, but it means that the label does not stand out in this characteristic relative to the other labels.

Table 1: Typical and untypical model characteristics for the five model labels: agent-based models (ABM), bio-economic models (BEM), ecological-economic models (EEM), social-ecological models (SEM) and system-dynamic models (SDM). The crosses mark the typical and untypical characteristics in each model label and grey shaded areas mark characteristics that render the respective model label distinctive (for further details, see text).

	ABM		BEM		EEM		SEM		SDM	
	typ.	untyp.	typ.	untyp.	typ.	untyp.	typ.	untyp.	typ.	untyp.
general										×
specific									×	
positive	×						×		×	
normative		×						×		×
understanding										
prediction									×	
participatory		×		×		×		×		×
spatial	×									×
dynamic	×		×				×		×	
stochastic	×			×						×
feedbacks	×								×	
agents	×					×				×
networks		×		×		×		×		×
asym. info		×		×		×		×		×
learning		×		×		×		×		×
utilitarian		×	×							×
non-classical	×			×		×		×		
non-linearity				×						
emergence				×		×		×		×
policy		×						×		
eq.-based		×	×						×	
algorithmic	×			×						×
analytical		×		×		×		×		×
numerical	×		×		×		×		×	

3.2 Relations between the models (question Q2 continued)

In the previous section the main similarities and differences between ABMs, BEMs, EEMs, SEMs and SDMs have been highlighted. According to Table 1, quite a lot of the 24 characteristics are either typical or untypical or neither of both in most or even all model labels. Only 12 instances were found where a model label is distinctive by a certain characteristic (grey-shaded cells in Table 1). The degree of overlap between the five model labels can be measured quantitatively by regarding the frequency distributions in Fig. 2 as vectors and calculating the Pearson's correlation coefficients between these vectors (Table 2).

The average correlation between a model label with the four respective others labels ranges from 1.8/4 = 0.45 (ABM) to 0.71 (EEM) and 0.74 (SEM). The highest pairwise correlation is between BEM and EEM (0.90), SEM and SDM (0.81) and SEM and EEM (0.80). These results identify quite a substantial overlap between the model labels, in particular between bio-economic, ecological-economic and social-ecological models. One may wonder whether this overlap also reflects in the journals in which the models were published. Comparing the diagonal cells of Table 3 with the off-diagonal cells reveals that for each model label the umber of "unique" journals in which no other model label was observed (given in the diagonal cells of the Table) is about equal to the number of journals in which also other model labels were found (given in the off-diagonal cells).

Table 2: Correlations between the model labels agent-based (ABM), bio-economic (BEM), ecological-economic (EEM), social-ecological (SEM) and system-dynamics (SDM), based on the frequency distributions in Fig. 2.

	ABM	BEM	EEM	SEM	SDM	Row sum – 1
ABM	1.00	0.20	0.39	0.71	0.50	1.80
BEM	0.20	1.00	0.90	0.62	0.67	2.39
EEM	0.39	0.90	1.00	0.80	0.73	2.82
SEM	0.71	0.62	0.80	1.00	0.81	2.94
SDM	0.50	0.67	0.73	0.81	1.00	2.71

Although the smallness of the sample size demands some caution, this indicates that the authors of different model labels partly prefer different journals to publish their papers but that there is also a substantial overlap through "shared" journals. The broadest journals in that sense, that contain more than two model labels, are *Ecological Economics* (containing BEM, EEM, SEM and SDM), *Ecological Modelling* (containing ABM, BEM, EEM and SEM), *Journal of Environmental Management* (containing ABM, BEM, EEM, SEM), *Proceedings of the National Academy of Sciences of the USA*, PNAS (containing ABM, BEM, SEM and SDM) and *Land Use Policy* (containing BEM, EEM and SEM).

3.3 Trends (question Q3)

The first part of the trend analysis is to relate the number of papers represented by each model label to the publication year (for the numerical values, see Appendix C in the Supplementary Material). Table 4 shows the average annual changes and their statistical significance obtained by linear regression. While BEMs, EEMs, and SDMs exhibit slight but highly insignificant declines, there is a weakly significant increase of about one ABM paper per year and a strongly significant increase of about two SEM papers per year. For comparison, for the years 2015–2019 the sum of the numbers of ABMs, BEMs, EEMs, SEMs and SDMs equals 27, 20, 24, 20, 31, reflecting in a (highly insignificant) average annual change of 0.8 (Table 4). Thus, SEMs increase significantly faster than the average of all five model labels while ABMs seem to exhibit an average growth.

Table 3: Journals or conference proceedings in which the 122 model papers have been published, sorted by the five model labels agent-based (ABM), bio-economic (BEM), ecological-economic (EEM), social-ecological (SEM) and system-dynamic (SDM). The diagonal cells contain the sources found only for the respective model label, while the off-diagonal cells contain the sources in which papers of the two respective model labels were found. Journals in which four (three) model labels were found are bold-faced (in italics).

	ABM	BEM	EEM	SEM	SDM
ABM	Ecol. Complex. Fishes Frontiers Ecol. Env. Frontiers Env. Sci. Proc. IEEE Conf.* Reg. Env. Change	**Ecol. Model.** **J. Env. Manag.** **PNAS**	**Ecol. Model.** **J. Env. Manag.**	Ecol. Appl. **Ecol. Model.** Env. Soft. **J. Env. Manag.** **PNAS**	**PNAS**
BEM		Aust. J. Agr. Res. Ec. Biol. Inv. J. Env. Econ. Manag. Nat. Res. Model.	Agricult. Syst. **Ecol. Econ**. **Ecol. Model.** **J. Env. Manag.** *Land Use Policy*	**Ecol. Econ.** **Ecol. Model.** **J. Env. Manag.** *Land Use Policy* **PNAS**	**Ecol. Econ.** IOP Earth & Env. Sc. **PNAS**
EEM			Adv. Syst. Sci. Appl. Aquaculture Biol. Cons. CEUR Works. Proc. Cons. Biol. Glob. Change Biol. IEEE Transact. Cyber. Syst. Res. Behav. Sci.	**Ecol. Econ.** **Ecol. Model.** Env. Res. Econ. Intl. J. Commons **J. Env. Manag.** *Land Use Policy*	**Ecol. Econ.**
SEM				Earth Syst. Dyn. Ecol. Appl. JASSS Marine Policy Ocean Coast. Manag. Sci. Total Env. Scientific Reports Sustainability (Switz.) Theor. Ecol. Urban Ecosystems	**Ecol. Econ.** **PNAS**
SDM					J. Cleaner Prod.

Proc. 2016 Comp.**

*Proceedings of the IEEE Conference on Decision and Control

**Proceedings – 2016 International Conference on Computational Intelligence and Applications, ICCIA 2016

Table 4: Average annual changes in the number of published papers within the time frame 2015–2019 for agent-based (ABM), bio-economic (BEM), ecological-economic (EEM), social-ecological (SEM) system-dynamic models (SDM), and all five model labels (All); and corresponding p-values from the underlying linear regression.

Model label	ABM	BEM	EEM	SEM	SDM	All
Annual change	0.8	–0.3	–0.1	1.8	–0.4	0.8
p-value	0.2	0.7	0.8	0.004	0.5	0.7

Analogously, Table 5 shows the trends in selected model characteristics (for the numerical values, see Appendix C in the Supplementary Material). Most characteristics exhibit insignificant trends with p-values above 0.2, while significant trends with p-values equal to or below 0.07 are observed only for the characteristics *general*, *stochastic* and *non-linearity*.

Table 5: Average annual changes in the number of published papers within the time frame 2015–2019 that contain a particular model characteristic, and corresponding p-values from the underlying linear regression. Only model characteristics with p-values ≤ 0.2 are shown.

Characteristic	Annual change	p-value
general	1.6	0.006
understanding	1.5	0.1
stochastic	1.5	0.07
agents	1.6	0.2
utilitarian	1.5	0.2
non-linearity	1.8	0.04
algorithmic	1.8	0.15
analytical	0.8	0.2

4 Discussion and Conclusions

4.1 Summary of the main results

122 papers dealing with the model-based integration of ecology and socio-economics in the fields of biodiversity conservation, ecosystem services and natural resource management from the years 2015–2019 were analysed with regard to 24 characteristics. The characteristics measure the purpose of the model study, structural features of the model, consideration of information, human behaviour, system complexity, environmental policy, as well as the formal implementation and analysis of the model.

In most model characteristics there is high variation among the models so that between 25 and 75 percent of the models have that characteristic and the complementary percentage does not (cf. Fig. 1). Rather frequently observed characteristics (> 75%) are: *positive analysis*, *dynamic*, and *numerical analysis*; while *networks*, *asymmetric information*, *learning in agents*, *non-classical agent behaviour* and *emergence* are considered only relatively rarely (< 25 %); and only very few studies are *participatory*. These observations do not seem to change over time, as a trend analysis shows (cf. Table 5): significant increases are found only in the characteristics *general*, *stochastic* and *non-linearity* which are quite abundant anyway in the sample.

Some of the large variation in the first-mentioned characteristics with occurrences between 25 and 75 percent is captured by the labels assigned to the models by the authors. The five most frequent labels found in the sample are “agent-based models” (ABM) (13), “bio-economic models” (BEM) (14), “ecological-economic models” (EEM) (23), “social-ecological models” (SEM) (25) and “system-dynamic models” (SDM) (8). In comparison to the other models, the ABMs have a high number of structural features and – next to the classical assumption of utility-maximising agents – also consider alternative models of human behaviour (although most of the ABMs do assume utility-maximising agents, confirming Groeneveld et al. (2017)) (cf. Table 1). Similar to observations made by Egli et al. (2019), emergence is also considered only in a minority of all ABMs in the sample. On the opposite end are the BEMs which contain only relatively few structural features and make use of a utilitarian framework such as the human model of *homo oeconomicus*. In between one can find the EEMs, the SEMs and the SDMs (which however also differ between each other, such that e.g., the SDMs rarely consider spatial structure, usually contain feedback loops and are often equation-based).

However, although there are differences between the models with different labels there are still many similarities, which can be seen in Fig. 2 and Table 1 – and is numerically confirmed by high pairwise correlation coefficients (taking the frequency distributions in Fig. 2 as vectors) (cf. Table 2). While ABMs somewhat differ, the other four model labels are correlated quite strongly, especially BEM with EEM, SEM with SDM, and SEM with EEM, with correlation coefficients ≥ 0.8.

That the ABMs are closely related to each other and somewhat different from the other model labels is also indicated by the results of a cluster analysis of the model characteristics. In Appendix D of the Supplementary Material, pairwise correlations between the model characteristics are calculated. Each characteristic is represented by a 122-element vector whose *k*-th element is one (zero) if the *k*-

th model in the sample of all models has (does not have) the characteristic. A high correlation between two characteristics *i* and *j* indicates that if characteristic *i* is present (absent) in a model then characteristic *j* is likely to be present (absent) in that model, as well. The two overlapping clusters D and E in Fig. D2 contain the characteristics *spatial*, *stochastic*, *algorithmic*, *agents* and *non-classical behaviour,* which are five of the typical characteristics of ABMs and exactly those five which render ABMs distinctive (Table 1). The other clusters in Fig. D2 cannot be mapped one-to-one to model labels. Clusters A and B contain many of those characteristics that are either typical or untypical for all 122 models (Fig. 1), while cluster C is difficult to relate and interpret.

The partial overlaps between the model labels indicated by Table 2 is also reflected in the journals in which the reviewed model papers have been published (Table 3). Although some journals were found to contain only one model label, a number of journals have published models of several labels – in particular *Ecological Economics*, *Ecological Modelling*, *Journal of Environmental Management* and PNAS which include four model labels each.

While there is a substantial overlap between the structure of the models within the different model labels, some differences exist with regard to temporal developments. While the number of published SEMs in the sample increased by about two per year, the numbers in the other model labels seem to remain rather constant (Table 4).

4.2 Evaluation of the main results

Addressing research question Q1, there appears to be quite a good balance between general and specific models, between positive and normative analyses, and between the model purposes of system understanding and prediction; also features like dynamics, spatial structure, stochasticity, agents and feedback loops are quite often considered. On the downside, issues that are likely to be relevant and complicate policy making in the real, such as asymmetric information, non-rational behaviour of agents and social networks, are rarely addressed; and despite calls for more participation of stakeholders in research, models are still very rarely used in participatory research. As the trend analysis in Table 5 indicates, this does not seem to change over time (addressing research question Q3).

Addressing question Q2, the labels attached to the models by their author(s) partly indicate a typical structure of the model, so that agent-based models (ABMs) tend to differ from the models with other labels, in particular the system-dynamic (SDM) and bio-economic models (BEMs). Explaining these differences between the models with different labels is clearly beyond the scope of the present paper. One explanation could be the disciplinary background (even though the 122 models were selected for interdisciplinarity) of the model authors. Although with different characteristics, Drechsler et al. (2007) and Drechsler (2020) compared in a similar way ecological, economic and ecological-economic models from the field of biodiversity conservation and found that the ecological models tended to contain more structural features and were more complex than the economic models.

On the other, despite these differences there is quite some overlap between the model labels, indicated by the correlation coefficients in Table 2, which reflect that, e.g., the models have similar purposes, share some structural features like dynamics, and share deficiencies like the wide absence of participatory applications. The overlap between the models also reflects in the observation that various journals include models of several labels. These observation can altogether be regarded as a positive signal, such that there seems to be enough diversity in the modelling cultures to avoid “inbreeding” but enough similarities to allow for communication and cross-fertilisation among different modelling communities.

A problematic observation, though, is that the number of papers with the present type of mechanistic models, designed to integrate ecology and socio-economics for the management of biodiversity and ecosystem services, grows only slowly (addressing research question Q3; cf. Table 4). Qualitatively this is confirmed by another Scopus search (not shown), carried out in June 2020, with the same search string as in section 2.1 and adding in turn the terms “agent-based”, “bio-economic”, “ecological-economic”, “socio-ecological” OR “social-ecological” and “system-dynamic”. Although the tedious manual screening described in section 2 was excluded for simplicity (so the two searches can be compared only loosely), the qualitative result is the same such that, except for SEM, the number of papers seems to remain constant over the past decade; while the number of SEM papers has increased from about 10 in 2010 to about 50 in 2019.

4.3 Limitations of the analysis and future research

The present study involves a number of limitations. The literature search via Scopus (section 2.1) will certainly not have found all the papers of the considered field. This is indicated, e.g., by the fact that the same search a few months later led to slightly different results. Further, the manual screening of the obtained papers may have not been free of any errors. In addition, the choice of the search terms is subjective and may have led to the omission of relevant articles. For instances, it did not yield any papers with *integrated models* that also contain applications in the field of environmental management.

Related to this is the fact that the selection of the model characteristics (section 2.2) is subjective, too. Smaller errors may have also occurred in the evaluation of the models with regard to the model characteristics (section 2.3). Although it is used only as a supplement to the correlation analyses described in section 2.4, the manual cluster analysis in Appendix D of the Supplementary Material involves subjective elements. Lastly, for time constraints only five years of data were considered which limits the significance of the results of the trend analysis (section 2.5).

While the errors in sections 2.2–2.4 are probably minor, the errors in the generation of the data base in section 2.1 and the trend analysis in section 2.5 call for further research. The use of alternative – possibly broader – search terms and a longer time frame could lead to interesting insights beyond those of the present study.

4.4 Conclusion

To conclude, mechanistic models integrating ecology and socio-economics for the management of biodiversity and ecosystem services by now consider quite a lot of system features such as spatial structure, agents and feedback loops, but are still largely (to varying degrees, depending on the model label) disregarding quite a number of issues such as the distribution and acquisition of information among and by the human actors, as well as the way in which the human actors translate available information into decisions. The human factor is also under-represented in the sense that only very few models are used within participatory studies. Nevertheless, there seems to be a fruitful level of diversity in modelling cultures but also sufficient overlap for cross-fertilisation, which may help further improving the models in the field.

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