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# To What Extent Can Agent-Based Modelling Enhance a Life Cycle Assessment? Answers Based on a Literature Review

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*ABSTRACT. Life cycle assessment (LCA) has proven its worth in modelling the entire value chain associated with the production of goods and services. However, modelling the consumption system, such as the use phase of a product, remains challenging due to uncertainties in the socio-economic context. Agent-based models (ABMs) can reduce these uncertainties by improving the consumption system modelling in LCA. So far, no systematic study is available on how ABM can contribute towards a behavior-driven modelling in LCA. This paper aims at filling this gap by reviewing all papers coupling both tools. A focus is carried out on 18 case studies which are analysed according to criteria derived from the four phases of LCA international standards. Criteria specific to agent-based models and the coupling of both tools, such as the type and degree of coupling, have also been selected. The results show that ABMs have been coupled to LCA in order to model foreground systems with too many uncertainties arising from a behaviour-driven use phase, local variabilities, emerging technologies, to explore scenarios and to support consequential modelling. Foreground inventory data have been mainly collected from ABM at the use phase. From this review, we identified the potential benefits from ABM at each LCA phase: (i) scenario exploration, (ii) foreground inventory data collection, (iii) temporal and/or spatial dynamics simulation, and (iv) data interpretation and communication. Besides, methodological guidance is provided on how to choose the type and degree of coupling during the goal and scope phase. Finally, challenging LCA areas of research that could benefit from the agent-based approach to include behaviour-driven dynamics at the inventory and impact assessment phase have been identified.*

KEYWORDS: Model coupling; Consequential LCA; Use phase; Human behaviour; Consumption and production

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## 1. Introduction

Worldwide, the modern economy generates pressures on the environment and strives towards more sustainable activities. The analysis of environmental impacts generated by an activity is addressed through a wide range of methodologies among which the life cycle assessment (LCA), a clearly accepted scientific methodology for quantitative assessment of product systems over their entire lifespan accounting for upstream impacts. LCA has been recognized for its ability to highlight environmental hotspots within a product system, to quantify and compare environmental impacts of products and services and to prevent burden shifting between impact categories or life cycle stages.

In LCA, the world is represented by a technosphere and an ecosphere (Hauschild, Rosenbaum and Olsen, 2018a); the ecosphere represents everything which is not intentionally “man-made” as opposed to the technosphere which represent everything that is used, created, or manipulated by humans. This technologically modified environment can be thought as a production system (PS), which refers to the inter-dependent activities required to deliver outputs/goods, and a consumption system (CS) which is the demand-driven exchange mechanism removing this output/good from the market availability, mainly driven by human attributes. LCA as currently practised, does not consider the cultural and regulatory contexts that can affect the consumption demand-driven mechanisms governing production. Economic models have been increasingly used to support the consequential approach of LCA on new products or emerging technologies (Earles and Halog, 2011). However, human choices are not always rational or driven only by economic factors (Garcia 2005); and as raised by Yang and Heijungs (2017), these models could benefit from the insights of behavioural economics. Although the entire value chain associated with a product is now well apprehended in LCA, the consumption system is modelled with simple hypothesis and averages, ignoring inter-individual behavioural variation (Polizzi di Sorrentino *et al.* 2016).

The environmental impacts of a system product can be strongly affected by various behavioural factors throughout its life cycle, from the choice between different alternative products to the use of the product and finally its disposal, as suggested by Polizzi di Sorrentino *et al.* (2016). Therefore, when considering product systems for which the environmental impacts are highly driven by behavioural attributes, the LCA representation of the production system

needs to be supplemented by a finer representation of the consumption system. Hellweg and Mila i Canals (2014) highlighted the necessity of including information that is based on consumer behaviour while modelling the use phase. However, modelling the consumption system remains highly challenging.

One way to generate behavioural data is statistically, such as with surveys, but the reliability is often limited by the sample size and missing data (Schmidt, 1997). Recent signs of progress have been made in computer science in the simulating complex systems and modelling user behaviour, which has already been conducted using different approaches: probabilistic methods (Jang and Kang, 2015), even data mining (D'Oca & Hong 2015) and agent-based modelling (Klein et al. 2012). Agent-based models (ABMs) are computational models that are composed of autonomous and heterogeneous entities, namely, agents (Epstein, 1999). The agent-based approach seems to be the most appropriate to model human behaviours since it considers the faculty of human beings to adapt, react and interact, led by their cultural and social backgrounds (Langevin et al. 2015). Contrary to black-box models such as those obtained by data-mining, ABMs provide an explicit and natural representation of the human behaviour which facilitates the understanding of the simulation and allows non-computer-science researchers to be part of the modelling process. Agents can interact with other agents in a dynamic environment and are endowed with rules that establish their behaviour. Behavioural models that are incorporated into ABMs can be merely reactive to stimuli (e.g., economic parameters) or can integrate a cognitive dimension (e.g., green consciousness). The complex real-world system is generated by the bottom-up modelling of the decision-making of agents. Phenomena can emerge at the macro-scale that traditional modelling techniques, such as differential equation-based, system dynamics and discrete event simulation, may potentially not be able to describe (Page et al., 2002). Besides, one of the main strength of the agent-based approach is its capacity to model a huge number of agents, allowing to reproduce real-world systems in a limited computational time. All of these reasons explain why the field of agent-based modelling has gained a significant following in recent years (Williams, 2018).

ABM has recently attracted attention as a complementary tool to LCA to model human behaviour and predict how the dynamics of a system can be affected by internal or external factors. Davis, Nikolic and Gerard P.J. Dijkema (2009) were the first to introduce the coupling of ABM with LCA to evaluate the sustainability of an emerging

energy infrastructure system. Since, several papers in which LCA and ABM are coupled have been published but existing literature is still scarce and heterogeneous. The first reason is that the computational improvements in the modelling of complex systems were made recently. In addition, the required expertise in both fields is not highly prevalent, as noted by (Marvuglia *et al.*, 2018). If ABM can contribute towards a better behavior-driven modelling in LCA, an overall picture of the coupling strengths and weaknesses is still missing to take full advantage of the capabilities of agent-based modeling for LCA methodology.

To fill this scientific gap, we propose a comprehensive review that compiles all papers related to the coupling of ABM and LCA. This review aims at screening how ABM and LCA have been coupled to date, in an effort to understand how it can help to improve LCA results and how this coupling can be achieved. We address the following specific objectives: (i) to compile all papers related to the coupling of ABM and LCA, (ii) to investigate how and why agent-based modelling has been used to support life cycle assessment in the literature, (iii) to establish what type of outputs ABM can generate for each product life cycle stage, (iv) to identify the methodological challenges at each LCA phase that can be tackled by ABM, and (v) to establish guidance on the coupling implementation. The first section presents the rationale for the selection of articles and the choice of the points of comparison. The second section analyses the selected papers according to these criteria. From this analysis, the theoretical opportunities and methodological issues are discussed in a third part, and future research needs are anticipated.

## **2. Materials and Methods**

### **2.1. Selection of articles**

This review intends to collect papers in which ABM and LCA have been coupled. A focus is carried out on all papers presenting a case study or a proof of concept in order to be able to analyse how the coupling was carried out from a methodological point of view. Since this concern is relatively new, no temporal restriction has been applied. The exhaustive search was performed with international bibliographic databases, Scopus, ISI Web Science, Science Direct and Google Scholar, with a combination of keywords relating to “Agent-based model\*” (or “ABM” or

102 “Multi-agent system” or “MAS”) AND “Life cycle assessment” (or “LCA” or “Life cycle analysis”). Articles using  
 103 the LCA acronym with another meaning (for example, local control agent or local configuration approximation)  
 104 were excluded.

## 105 **2.2. Analysis grid**

106 The analysis follows the four steps of the LCA methodology as defined by (ISO 14040:2006): goal and scope  
 107 definition, life cycle inventory collection (LCI), life cycle impact assessment (LCIA) and interpretation of the  
 108 results. To analyse the use of both LCA and ABM, sets of criteria that are specific to each tool and specific to the  
 109 coupling were selected. ABM criteria, as well as criteria that are specific to the coupling of both tools, have been  
 110 included in the analysis grid by drawing an analogy between the four LCA methodological phases and the seven  
 111 steps of the description of an agent-based model, as formalised by (Bouquet *et al.*, 2015). Table 1 summarises the  
 112 set of the selected criteria, and the following sections detail them.

113 *Table 1 Description of criteria considered within the review*

	Specific to LCA	Specific to ABM	Specific to coupling
Goal and scope	. Goal (aim, rebound effect) . Scope (temporal consideration, life cycle steps, modelling methodology)	. Purpose of ABM use . Agents (type, number, attributes) . Time step	. Feedback loop . Type of coupling . Degree of coupling . Affected parts of the LCA computational structure
Inventory	. Foreground/Background data	. Model inputs	. Data exchange (type, management)
Impact assessment	. LCIA methods (mono/multi-criteria, dynamic)	. Formalization (decision process, agents' capabilities)	. N/A
Interpretation	. Uncertainty/Sensitivity analysis	. Validation/Calibration . Graphical output	. Comparison with conventional LCA studies

114 To understand if the way that coupling has been performed (the type and degree of coupling) is determined by the  
115 choices that have been made during the goal and scope phase, we used the statistical method called principal  
116 component analysis (PCA). The method and the results of this analysis are presented in the Supporting Information.

### 117 **2.3. Criteria for Goal and Scope**

118 **LCA Goal.** The goals of the studies are compared to identify papers that intend to address policy recommendation,  
119 explore emerging technologies or assess innovative product development. We investigate whether studies include  
120 the rebound effect. A rebound effect refers to the potential change in user behaviour or consumption patterns  
121 induced by technological improvements (Binswanger, 2001). For example, energy-efficient technologies induce a  
122 drop in cost that stimulates an increasing consumption of this technology (direct rebound effect) and/or increases  
123 consumption of other products due to cost savings (indirect rebound effect), as discussed by (Sorrell and  
124 Dimitropoulos, 2008).

125 **LCA Scope.** The analysis of the scope definition includes (a) the temporal consideration (i.e., current context or  
126 future outcomes), (b) the life cycle steps considered, and (c) the modelling methodology. Two main modelling  
127 principles can be used when performing an LCA: attributional or consequential. As described by the handbook *LCA*  
128 *in theory and practice* (2018), the attributional LCA (ALCA) quantifies how severely a process impacts the  
129 environment to understand the origin of the burden. ALCA considers the product system to be isolated from the  
130 rest of the technosphere and/or the economy. On the contrary, consequential LCA (CLCA) has been developed to  
131 study change-oriented processes to quantify the consequences of a choice on the environment. CLCA includes every  
132 activity that is affected by a change throughout the life cycle of the product system that is being studied. These  
133 activities are not necessarily within the life cycle of the product system.

134 **Purpose of the use of ABM.** A qualitative analysis of the purpose of the use of the agent-based approach is  
135 performed.




136 **ABM agents.** We investigate how agents are implemented, including the type, number and attributes of the agents.  
 137 Two types of attributes are distinguished: characterization attributes that are constant during the simulation and  
 138 dynamic attributes that evolve at each time step of the simulation according to the environment.

139 **ABM time step.** The time step that is used to run the simulation is an essential parameter in any ABM since it  
 140 highly depends on the phenomena it aims at modelling, and in return, it highly influences the computational time  
 141 (Helbing, 2012).

142 **Feedback loop.** We investigate whether a feedback loop is implemented or not. A feedback loop is defined as the  
 143 integration of LCA results in the cognitive architecture of the ABM agents, e.g., to integrate the awareness of the  
 144 environmental impact of their choice to their decision-making process.

145 **Type of coupling.** The way in which ABM and LCA are coupled is referred to as the *type of coupling*, and it is  
 146 examined to understand the internal working of each model, such as if a data flow is exchanged between both  
 147 models or if both models are embedded in one another. We define three different coupling strategies in compliance  
 148 with the approach of Udo de Haes et al. (2004): model integration, hybrid analysis and complementary use  
 149 (described in Table 2). Instead of the term “model integration”, Udo de Haes et al. refers to “extension of LCA,”  
 150 although this fourteen-year-old term has since been supplanted (Marilleau, 2016).

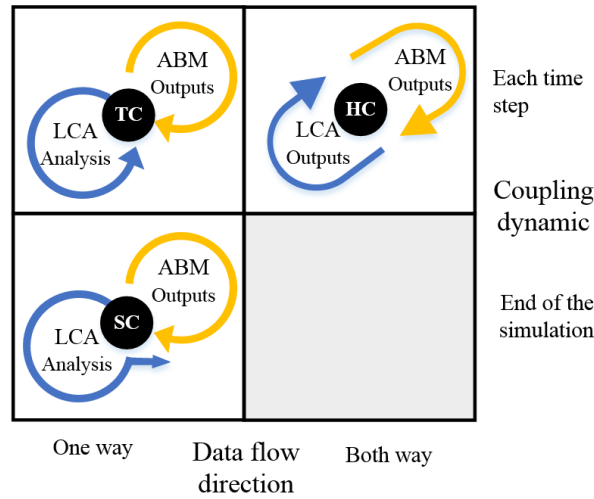
151 *Table 2 Description of the different types of coupling (yellow and blue circles represent agent-based and life cycle assessment models,*  
 152 *respectively; yellow and blue arrows represent data flow from agent-based and life cycle assessment models, respectively)*

	Type of coupling	Coupling strategy
	Model integration	One unique and larger model created from the combination of models
	Hybrid analysis	Flexible combination of models that exchange data between one another
	Complementary use	Separate models used in combination; results are calculated separately



**Degree of coupling.** The degree of coupling characterises the flow of the exchanged data; thus, it is only appropriated for model integration and hybrid analysis. When separate models are used in combination, they do not exchange any information, and the degree of coupling has been referred to as *Complementary*. Models can be coupled differently according to (a) time (at which time step they exchange information) and (b) direction (in which way the data are exchanged). We defined three degrees of coupling as described in Figure 1: hard, tight and soft-coupling. The term “hard-coupling” was first used by (Marvuglia *et al.*, 2017) to define the degree of coupling they are using, which is why the choice has been made to say “soft” as opposed to “hard”, and “tight” is used to express an intermediate interdependence of both models.

- . *Soft-coupling*: ABM outputs obtained at the end of the simulation are aggregated and are used as inputs for LCA analysis.
- . *Tight-coupling*: ABM outputs are used as inputs of the LCA at each time step.
- . *Hard-coupling*: Data are exchanged between LCA and ABM at each time step (LCA results are used as an input parameter for the ABM simulation)

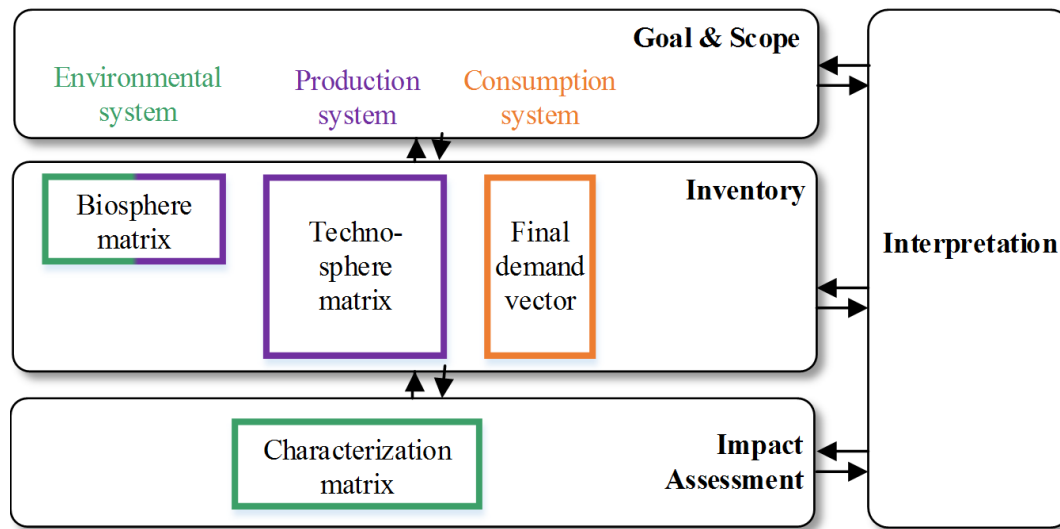


166

167 *Figure 1 Description of the different degrees of coupling according to the coupling dynamic and the data flow direction (SC stands for soft-*  
 168 *coupling, TC for tight-coupling, HC for hard-coupling; the grey square is not applicable)*

**Affected parts of the LCA computational structure.** Within the context of LCA, ABM can be used to simulate different types of systems: production system, consumption system or environmental system. As introduced in the

171 introduction, the production system refers to the assembly of activities that are required to transform inputs into  
 172 deliverable outputs (goods or services), from the supply chain to the market. Once removed from the market, the  
 173 consumption of finished products and services can be described by the frequency, the quantities of products that are  
 174 consumed and the way the product is used. The environmental system (ES) is the assembly of mechanisms that link  
 175 human-made interventions in different media (air, soil, water, and biota) to a set of areas of protection. The system  
 176 modelled by ABM delimits the part of the LCA computational structure that is affected by this coupling (Figure 2).



177  
 178 *Figure 2 Representation of the computational structure within the four distinct LCA phases as defined by ISO 14040 and 14044 standards*  
 179 *(rectangles are scaled to represent matrices of size  $n \times n$ )*

180 Heijungs and Suh (2002) clarified the computational structure of LCA by introducing a matrix-based formalism for  
 181 both inventory and impact assessment steps. These researchers defined that inventory (i.e., the quantity of emission  
 182 released into each compartment and extracted resources) can be assessed thanks to three matrices: the technosphere  
 183 matrix, the biosphere matrix and the final demand vector (Figure 2). The  $(n)$  technology-based processes, as well  
 184 as their interactions with one another, are defined in the technosphere matrix, which is a square matrix of size  $n \times n$ .  
 185 A row quantifies the economic flows that a process has with all the other existing process. The biosphere matrix  
 186 details the elementary flows ( $m$ ) that are released or are consumed by each technological process. It is an  $m \times n$  matrix  
 187 in which a row indicates from which processes an elementary flow is emitted, whereas a column illustrates all of  
 188 the elementary flow released by a process. The biosphere matrix is represented with both green and purple colours,

189 because part of the fate of pollutants can be addressed in the inventory phase through the biosphere matrix and,  
190 therefore, are dependent on the environmental system. The final demand vector (size  $n$ ) corresponds to the number  
191 of goods required. Once all of the elementary flows (emissions and extracted resources) have been determined in  
192 the inventory phase, methods should be selected to assess the burden they represent for the environment according  
193 to different impact categories ( $p$ ). The substance contribution to the environmental system is calculated due to the  
194 characterization matrix of size  $m \times p$  (Figure 2). A row is composed of the characterisation factors of the respective  
195 emission that is associated with each impact category.

## 196 **2.4. Criteria for Inventory**

197 **LCA foreground/background data.** The inventory phase of the LCA is the collection of data on flows going in  
198 and out of the system to assess all of the elementary flows (emissions to air, soil and water as well as resources  
199 extraction). A distinction is made between the (a) foreground data (i.e., data on the processes under control of the  
200 decision maker) and the (b) background data (i.e., data on processes that are part of the system but over which the  
201 decision maker has no direct control). The analysis investigates the source of both types of data.

202 **ABM inputs.** A comparison of the input parameters that are required to perform the agent-based simulation is  
203 carried to spot based on (a) the quantity of data needed, (b) the potential difficulties in obtaining them and (c) their  
204 specificity to the temporal and spatial context of the study.

205 **Data exchange.** This criterion explores what type of data is generated by the ABM and at which life cycle stage  
206 these outputs are used in the selected articles. Then, we examine how the models are physically interconnected by  
207 comparing the chosen exchange protocol that is selected to transfer data between both models. Coupling two models  
208 requires that attention is given to two points: conformity of the structure of the exchanged data and consistency of  
209 their content.

## 210 **2.5. Criteria for Impact Assessment**

211 **LCIA.** According to ISO 14040 (2006), the LCIA phase follows two steps: (1) selection of impact categories and  
212 (2) characterization of the impacts of the emissions and resources based on the selected impact categories. The

213 studies are compared according to the impact and damage categories that have been chosen (the study is referred to  
214 as mono-criteria when only one impact category has been selected). The criteria that are used for comparison  
215 between the different case studies is whether the authors use a dynamic impact assessment method, which is to say,  
216 whether the characterization matrix (as defined in Figure 2) is affected by the coupling and, if so, which  
217 environmental mechanism is dynamically modelled.

218 **ABM formalization.** This criterion aims to investigate how the agents' decision-making process is formalized. The  
219 capabilities of an agent are defined as: (1) reactivity: the agent can perceive its environment and to adapt its  
220 behaviour to satisfy its objectives; (2) pro-activeness: it exhibits goal-oriented behaviour and takes initiative to  
221 satisfy its objectives; (3) social ability: it can interact with other agents to satisfy its objectives. If these three  
222 capabilities are met, the agent is considered to be "intelligent" as defined by Wooldrige (2009).

## 223 **2.6. Criteria for Interpretation**

224 **LCA Uncertainty/Sensitivity Analysis.** The LCA methodology aims to evaluate potential impacts, and the  
225 reliability of the results strongly depends on the uncertainties that are associated with the selected assumptions  
226 (Huijbregts, 1998). The analysis of the interpretation phase involves whether a sensitivity check has been performed  
227 (i.e., sensitivity analysis and uncertainty analysis). An uncertainty analysis aims to explore the variability of the  
228 overall outputs, while the sensitivity analysis investigates from which parameters the variability comes from.

229 **ABM Validation/Calibration.** The corpus of articles is examined through validation, which is a fundamental  
230 procedure of having enough confidence in the model to use it as part of a decision-making tool and/or with  
231 predictive capacity. Amblard et al. (2007) define two levels of validation: internal and external. Internal validation  
232 ensures that the model is robust and that the parameters are differentiated. This is achieved by exploring the model  
233 properties through a sensitivity analysis, for example. External validation is the ability of the model to correctly  
234 measure and/or predict the phenomena for which it has been developed. This step is usually undertaken by  
235 comparing ABM outputs with empirical data.

236 **ABM Graphical Output.** We determine whether the reviewed studies exploit the ability of ABMs to produce  
237 graphical outputs.

238 **Comparison with conventional studies.** We check through the whole corpus to determine whether a comparison  
239 with conventional existing LCA studies has been made to quantify the relevance of coupling LCA with ABM.

### 240 3. Results

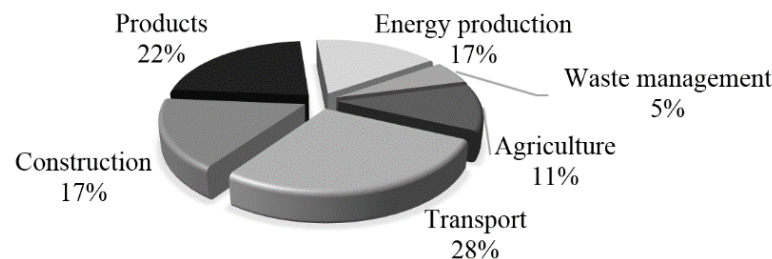
#### 241 3.1. Selection of articles

242 In total, 31 articles dealing with ABM and LCA were found according to the procedure detailed in the material and  
243 method section, as shown in Figure S1 (Supplementary Information), and the exhaustive list can be found in Table  
244 S1(Supplementary Information). The thirteen articles detailed below were not further considered in the detailed  
245 analysis since they do not present a case study:

- 246 - Four papers are categorized as “review papers.” One critical review that focusses on the uncertainty in ABM  
247 and LCA-coupled models was found (Baustert and Benetto, 2017). Marvuglia *et al.* (2018) reviewed the  
248 existing agricultural agent-based models and their implementation to support LCA. A comparison between the  
249 use of ABM and game theory in a predictive application of LCA on emerging systems was made by Alfaro et  
250 al. (2010), while McCabe and Halog (2016) explored the potential of different participatory modelling  
251 approaches, including ABM, to allow stakeholder consideration and behavioural simulations in social life cycle  
252 assessments.
- 253 - Several case studies are covered by two or more papers. The paper by (Navarrete Gutierrez *et al.*, 2015a) was  
254 also covered by (Marvuglia *et al.*, 2016), who made a return on experience. In the same way, the framework of  
255 Davis et al. was developed in two papers, but only the peer-reviewed one (Davis et al. 2009) was studied,  
256 whereas the conference proceeding (Davis, Nikolic and Dijkema, 2008) was left aside. Finally, three papers  
257 from Attallah et al. were found, and all deal with the same case study, while only the most recent and exhaustive  
258 one (Attallah et al. 2014) is considered. Therefore, these four additional papers were disregarded in our analysis.

- Five papers present their framework without applying it to a real case study. They are categorised as framework papers in Figure S1 and were eliminated from the analysis. Mo et al. (2014) developed a framework to consider each life cycle step of the LCA (from production to disposal) as an independent agent with its characteristics. Knoeri et al. (2013) proposed a dynamic criticality assessment for raw materials in which the materials' stocks and flows are simulated with an agent-based approach, and the environmental impacts of substitution decisions are theoretically quantified due to LCA. Zudor and Monostori (2001) introduced a framework to consider environmental impacts during the allocation process due to an agent-based model, but it had not implemented the environmental part to date. In the same way, Choong and McKay (2014) worked with agent-based modelling to simulate the interactions and behaviours of the different processes that are involved in the palm oil supply chain. The final goal is to identify the key requirements to improve resource-use efficiency while reducing energy consumption and to trace back information to implement eco-labelling. However, the article only presents the results of the simulation of the palm oil industry supply network but does not assess any LCA to date. Latynskiy et al. (2014) evoked in their conference proceeding expected results from the simulation of a low-carbon agriculture policy and the associated reduced greenhouse gas emissions.

Finally, the review focuses on 18 case studies that are analysed according to the established set of criteria. Davis et al. (2008) were the first to theorize the coupling between ABM and LCA in 2008. The growing interest in this subject is palpable, since the research shows a rising trend in the number of annual publications. The articles are relatively equally distributed among the different sectors under the study, as illustrated by Figure 3. This partition suggests that there is not a field that is more suitable for ABM and LCA coupling.



*Figure 3 Fields of study of the corpus*

279 Table 3 presents the key points of the analysis grid for the 18 selected articles, and the complete evaluation grid is  
280 provided in the Supplementary Material.

281

Authors	Product system	Goal	Life cycle steps	Rebound effect	Feedback	Modelling methodology	Justification for the use of ABM	Agents' type	Agent's attributes	Simulation duration	ABM time step
<b>Walzberg et al., 2018</b>	Smart homes	Accounts for the rebound effect when assessing the environmental performance of smart homes	use phase	yes	no	consequential	to integrate irrational decisions	Households + Electrical appliances	Households: pro-environmental attribute (dynamic); Electrical appliances: electric consumption (static)	1 year	1 hour
<b>Vasconcelosa et al., 2017</b>	Carsharing system	Policy analysis for different carsharing system configurations	use phase	no	no	consequential	explore "what-if" scenario	Travelers + Carsharing operator + Vehicles + staff	Travelers: gender, income, driver's license, car, motorcycle, parking space (all static)	not mentioned	not mentioned (<15minutes)
<b>Mashhadi et al., 2017</b>	Personal computer with smart-meters	Uncertainties and heterogeneity in the use phase (proof of concept on PC with feedback)	use phase	no	no	both	to integrate irrational decisions	Households (=one consumer)	Environmental friendliness (static), behavioural control (static), social pressure (dynamic), habit (dynamic)	401 days	1 day
<b>Lu et al., 2017</b>	Speed railway	Policy analysis for developing high-speed railways	resources extraction, fuel production, vehicle manufacturing, infrastructure construction, use phase	no	no	consequential	to capture spatial and temporal adoption/market dynamics	Travelers	Minimum satisfaction (dynamic), maximum uncertainty (dynamic), uncertainty tolerance level (static)	not mentioned	not mentioned
<b>Onat et al., 2017</b>	Battery electric vehicles	Sustainable policies for battery electric vehicles	use phase (well-to-tank and tank-to-wheel)	no	no	attributional	to capture spatial and temporal adoption/market dynamics	Consumers + Government + Vehicles	Social acceptability (dynamic)	not mentioned	not mentioned
<b>Wu et al., 2017</b>	Green building	Policies analysis for green building development	construction phase + operational phase	no	no	consequential	to integrate irrational decisions	Government + Developers + General public	General public: environmental awareness (dynamic); Developers: Green or Conventional (dynamic)	20 years	1 year



<b>Pambudi et al., 2016</b>	Plastic waste	Appropriate strategies of plastic recycling through environmental and social aspects	end of life	no	no	attributional	to integrate irrational decisions	Consumers	Willingness to change	not mentioned	not mentioned
<b>Bustos-Turu et al., 2015</b>	Plug-in Electric vehicle	Find optimal strategies for PEV charging	resource use, production and operational phase	no	no	consequential	to capture spatial and temporal adoption/market dynamics	Travelers	Worker/non-worker	1 day	10 minutes
<b>Bichraoui-Draper et al., 2015</b>	Switchgrass-based bioenergy system	Farmers' potential adoption of switchgrass as a biomass	production, delivery	no	no	attributional	to capture spatial and temporal adoption/market dynamics	Farmers + Refineries + Cofired generators plants	Age (dynamic), education (static), risk aversion (dynamic), familiarity (dynamic)	50 years	1 year
<b>Navarrete Gutiérrez et al., 2015</b>	Biomethane production	Policy implementation for biomethane generation with consideration of social factors (evolution of the agricultural system)	production	no	yes	consequential	to integrate irrational decisions	Farmers + Farms + Product buyers	Green consciousness (static)	not mentioned	1 year
<b>Querini et al., 2015</b>	Electric vehicles	Policy analysis for mobility (electric vehicles)	production, use, end of life	no	no	consequential	to integrate irrational decisions	Travelers	Typologies based on daily activities: commuter/inactive/retired (dynamic)	8 years	1 hour
<b>Hicks et al., 2015</b>	Lights	Explore extent and time lags of efficiency gains as well as the rebound effect thanks to efficient lighting technologies	use phase	yes	no	attributional	to integrate irrational decisions	Consumers	Typologies based on the relative importance of six factors when selecting a new light (static)	18 years	1 year

<b>Wang et al., 2014</b>	Drinks	Environmental impacts of beverage consumption	production, distribution, use, end of life	no	no	attributional	to capture spatial and temporal adoption/market dynamics	Consumers	Environmental friendliness (static)	100 days	1 day
<b>Attallah et al., 2014</b>	Certification credits	Assess the consequences of sustainable policy on certification credits for buildings	use phase	no	no	attributional	explore "what-if" scenario	Client+Project + Consultants + Contractors	Client: governmental or private; Project: location, price; Consultant: experienced or not, Contractors: HSE plan or not	not mentioned	not mentioned
<b>Miller et al., 2013</b>	Switchgrass	Explore switchgrass adoption (product)	production phase	no	yes	both	explore "what-if" scenario	Farmers	Resistance to change (static), profitability (dynamic), familiarity with the technology (dynamic)	20 years	1 year
<b>Heairet et al., 2012</b>	Switchgrass	Analyse at the local level the development of bioenergy supply chains (switchgrass biofuel and bioelectricity markets)	production, transportation, processing, use	no	no	attributional	explore "what-if" scenario	Farmers + refineries + electric generators	Risk tolerance (static) and social acceptance threshold (static)	not mentioned	1 year
<b>Davis et al., 2009</b>	Biomass electricity production	Explore biomass as electricity production (technology)	biomass production, transportation, processing, conversion to electricity	no	yes	attributional	to capture spatial and temporal adoption/market dynamics	Firms (the entity that operates the technology) + Fossil-based power plants	Efficiency ratio, production capabilities	19 years	1 year
<b>Xu et al., 2015</b>	Books	Explore books e-commerce market and the rebound effect of increased buying power of consumers	transportation (driving to bookstores or delivering)	yes	no	consequential	to capture spatial and temporal adoption/market dynamics	Consumers	Preference, leadership, social need, need satisfaction, uncertainty	13 years	1 year

### 3.2. Goal and scope

**LCA Goal.** We can identify three different types of goals. (i) Forty-four percent of the papers aimed to help decision-making for sustainable policy implementation. For example, Lu and Hsu (2017) investigated different incentives-based scenarios for the implementation of the high-speed railway Guangzhou-Shenzhen-Hong Kong in 2020: they first assessed the ticket fare that would result in the lowest environmental impact of the high-speed train, and second, they proposed a scenario without through train with which the greenhouse gases emissions were reduced by 25%. (ii) Twenty-two percent of the studies aimed to better describe the use phase. Since the environmental impact of electrical appliances highly depends on the consumption pattern (e.g., time of use and power management after usage), Mashhadi and Behdad (2017) propose an ABM to simulate consumption patterns according to different user typologies and to further quantify the variability of the resulting LCA. (iii) The last 28% of articles explores how emerging technologies could impact the environment by analysing how their supply chain and market penetration would potentially develop. Heairet et al. (2012) studied the environmental impact of the developing bioenergy industry due to an ABM that models each actor in the supply chain: the farmers for switchgrass biofuel production, biofuel refineries and electric generators for the bioelectricity market.

Three studies model rebound effects (Xu *et al.*, 2009; Hicks, Theis and Zellner, 2015a; Walzberg *et al.*, 2018). Walzberg, Samson and Merveille (2018) model both the direct and indirect rebound effect that can occur in smart homes. They use an ABM to compute at each time step the monetary savings that result from the consumption pattern of each household and further exploit the Canadian Input-Output tables to reallocate these savings in other economic sectors. The authors quantify that the indirect rebound effect increases 24% of the use phase impact on climate change. Hicks, Theis and Zellner (2015b) use the ABM to assess the increase in electricity consumption (direct rebound effect) that results from the adoption of energy-efficient lighting technologies. These researchers account for different agent typologies (as a function of preference, misinformation) and several policies. Xu et al. (2009) use ABM to simulate the dynamics of the book market following the introduction of a self-pick-up option. The authors evaluate the direct rebound effect on transport resulting from the purchase of e-books instead of conventional books. The agent-based approach allows the authors to model the rebound effect as a function of the

individual choices made by the cognitive agents between both options and were able to quantify a decrease of 12% gasoline consumption per book with a self-pick-up option.

**LCA Scope.** Half of the studied articles have a predictive approach and forecast possible outcomes with a time horizon to 2020 for five articles (Xu *et al.*, 2009; Miller *et al.*, 2013; Bichraoui-Draper *et al.*, 2015; Florent and Enrico, 2015; Navarrete Gutierrez *et al.*, 2015a). Hicks et al. (2015) forecast potential environmental impact savings from the shift to efficient lighting technologies (compact fluorescent lamp and light-emitting diode) until the year 2083, which represents the most extended forecasting period of the corpus.

Regarding the life cycle steps considered, one-third of the studies only consider the use phase of the product system, either because previous LCAs have shown that the use phase of the product system is the most impactful phase (Attallah, 2014; Onat *et al.*, 2017; Vasconcelos *et al.*, 2017), or because the study aims to quantify the environmental impacts that are associated with the heterogeneity of the consumption/usage pattern (Hicks, Theis and Zellner, 2015b; Raihanian Mashhadi and Behdad, 2017; Walzberg *et al.*, 2018).

Half of the corpus uses a consequential modelling methodology, among which two studies specify that both attributional and consequential methodologies can be used (Raihanian Mashhadi & Behdad 2017; Miller et al. 2013), and seven studies do not specify the modelling methodology (Xu *et al.*, 2009; Navarrete Gutierrez *et al.*, 2015a; Querini and Benetto, 2015; Bustos-Turu *et al.*, 2016; Lu and Hsu, 2017; Vasconcelos *et al.*, 2017; Walzberg *et al.*, 2018). We classified their modelling methodology as consequential, since ABM is used to investigate the change of demand for products that are not in the system boundary of the product system under study. Therefore, the product system is not isolated from the rest of the economy. For example, Lu et al. (2017) studied the environmental impacts of the introduction of a high-speed railway, and the authors use ABM to quantify to what extent this transportation mode displaced the other modes. These CLCAs only consider the consequences of the introduction of an innovative product/emerging technology on its market share. ABM is used to assess direct consequences on the foreground consumption system. Indirect changes in the activities all along the supply chain of the product system (the response of the production system to the consumption demand) that can be affected by

333 the displacement effect are not considered, except from the research of Walzberg et al. (2018), which includes an  
334 indirect rebound effect.

335 **Purpose of ABM use.** We can identify three main reasons that justify the use of ABM in environmental studies: (i)  
336 to explore a *what-if* scenario, (ii) to capture spatial or market dynamics and (iii) to integrate irrational and social  
337 behaviours. (i) Four studies take advantage of the ability of ABM to explore scenarios *via* the simulation of different  
338 system configurations. Wang, Brême and Moon (2014a) use ABM to set up 6 scenarios representing different  
339 configurations of the beverage consumption resulting either from government incentives (“bottled water is banned”)  
340 or environmental constraints (“no tap water available due to pollution”). (ii) Thirty-nine percent of the studies use  
341 ABM mainly to explore spatial and temporal dynamics. For example, Wu et al. (2017) compare the environmental  
342 impact of green buildings development in a hypothetical city under a fixed percentage in specified neighbourhoods  
343 with a pattern emerging from the ABM simulation (developers decide on the new buildings’ type and location).  
344 Green buildings can be located in neighbourhoods with low environmental friendliness to raise awareness or, on  
345 the contrary, with high environmental friendliness to ensure a high return on investment. Wu et al. demonstrated  
346 that the impact results are highly dependent on the spatial layout of the green buildings: nonrenewable energy saved  
347 during the operational stage is reduced when green buildings are located in an area with high environmental  
348 awareness throughout the population, rather than when they are placed with the educational goal to raise awareness.  
349 Besides spatial dynamics, market dynamics can be captured by ABM to assess the environmental impacts of  
350 innovative products. It is worth mentioning that LCA has been performed in these studies to compare products,  
351 rather than to find change levers for a more environmentally friendly design. For example, using an ABM, Lu and  
352 Hsu (2017) simulated the market share for different transport modes (aircraft, bus, train) after the introduction of a  
353 high-speed railway. The environmental impact of each transport mode was calculated by the occupancy rate. (iii)  
354 Economic models are able to assess market dynamics for emerging products; however, they are all based on the  
355 principle that humans are rational. ABM turns out to be an effective approach to integrate irrational choices that are  
356 driven by socio-economic, -demographic and -cultural factors. This point is highlighted by 37% of the articles in  
357 this corpus to justify their use of the agent-based approach. *Farmer* agents in Bichraoui-draper (2015)’s work are

defined by social (age, education, risk aversion, familiarity) and economic (potential profit) attributes. However, the small correlations ( $<0.20$ ) between the social factors and the CO<sub>2</sub> emissions during the growth of the crops, ethanol generation, electric generation and ethanol distribution processes show that individual attributes have little influence on the LCA scores, contrary to the economic factor *potential profit* (correlation of 0.67).

**ABM agents.** All papers model cognitive agents (i.e., with a decision-making skill) that are able to represent humans, either as individuals (e.g., farmers and consumers) or as entities (e.g., households and firm). Papers with a product focus design agents as consumers (e.g., Raihanian Mashhadi & Behdad 2017b; Hicks et al. 2015b; Xu et al. 2009; Wang et al. 2014b), and studies with a policy analysis model agents as entities government (e.g., Susie Ruqun Wu et al. 2017; Onat et al. 2017), or companies (Attallah *et al.*, 2014; Vasconcelos *et al.*, 2017). Twenty-two percent of the articles also represent processes of the supply chain of the product system by using technological agents. In the same way as cognitive agents, these technological agents can be of two types: devices (e.g., vehicles in Vasconcelos et al.'s article (2017)) or firms/economic entities (for example refineries, power plants or generators (Heairet et al. 2012; Bichraoui-Draper et al. 2015)).

Cognitive and technological agents can (i) interact among them, (ii) interact with other types of agents and (iii) interact with the static supply chain, if one has been previously defined by databases. These interactions are an essential driver of the decision-making process. In Wu et al.'s agent-based model, green building coverage is driven by the interactions between the government, the inhabitants and the developers. Developers are encouraged by the incentives set each year by the government and by public perception to move towards green building construction. Households' environmental awareness evolves at each time step as a function of their neighbours.

One of the key specificities of ABMs is the high number of agents that can be simulated. Vasconcelos *et al.* (2017) simulate as many travellers as inhabitants in Lisbon, which are 547733. The number of agents, as well as their attributes, can be static or evolve during a simulation. For example, the number of agents as *Developers* in Wu's agent-based model is a function of the *Public* agents' environmental awareness, which is an attribute that evolves at each time step. For agents with the most advanced cognition, the decision-making process is driven by the combination of several attributes. Environmental awareness is the attribute the most frequently used among the

383 cognitive agents to generate pro-environmental behaviours, as well as the potential spread of a green consciousness  
384 (Attallah, 2014; Wang, Brême and Moon, 2014b; Hicks, Theis and Zellner, 2015b; Navarrete Gutierrez *et al.*,  
385 2015a; Mashhadi and Behdad, 2017; Susie Ruqun Wu *et al.*, 2017; Walzberg *et al.*, 2018).

386 **ABM time step.** The time step varies from an hourly period to a yearly period. The choice of the time step can be  
387 justified either by (i) the scope of the analysis (Navarrete Gutierrez *et al.* (2015a) uses this time step as it fits well  
388 the farming period) or (ii) the trade-off between computation-time and level of detail needed. Since Hicks *et al.*  
389 (2015b) study a product with a 5-year lifetime, a one-year-time step enables a fine-grain model without being too  
390 time-consuming (the system is replaced every five time-steps, and the total simulated period is 70 years). A third  
391 of the corpus adopted a one-year time step. None of the articles evoke the computational time of their model.

392 **Feedback loop.** Four articles use a feedback loop (Davis, Nikolic and Dijkema, 2009; Miller *et al.*, 2013; Navarrete  
393 Gutierrez *et al.* 2015b, Walzberg *et al.* 2018). In Miller *et al.* 's work (2013), the decision process integrates the life  
394 cycle inventory results of the previous time step. However, the criterion that is sent back to the ABM is not specified.  
395 In the same way, in Davis, Nikolic and Dijkema's model, each agent knows the LCA score that is associated with  
396 its previous actions/configurations. The authors only mention a criterion based on the reduction in the CO<sub>2</sub> emission  
397 as an example. Navarrete Gutierrez *et al.* (2015b) proposed a static feedback loop: *farmer* agents have a knowledge  
398 of the crops' LCA score calculated at the beginning of the simulation. Finally, Walzberg, Samson and Merveille  
399 (2018) model smart meters, which are devices that provide electricity consumption information in real time to the  
400 inhabitants and optimize their load scheduling. The agents *Occupants* only receive a feedback on energy  
401 consumption; however, the technological agents *Devices* adjust at each time step their load scheduling according to  
402 feedback on their environmental impact.

403 **Type of coupling.** Regarding the type of coupling:

- 404 - Four papers do not mention the type of coupling they use.
- 405 - Complementary use has been experimented in two studies. ABM and LCA were used separately by  
406 Pambudi *et al.* (2016) and Onat *et al.* (2017). In these cases, ABM was used to determine the rate of adoption

of several potential waste management systems (respectively electric car) since the community (respectively consumers) involvement and acceptance are necessary to assess sustainable plastic waste management (respectively battery electric vehicles), while LCA was used to assess the environmental impact of the different strategies. LCA results are not scaled according to this adoption rate.

- LCA and ABM are integrated in seven studies. Davis, Nikolic and Gerard P.J. Dijkema (2009) were the first to extend LCA with ABM: in their model, the static LCA database can be considered as a *WorldMarket* agent with which the other *Technological* agents can interact. The same procedure was used by Walzberg et al. (2018). The authors represented some of the system processes from the LCA database ecoinvent 3.1, such as *Appliances* agents evolving at each time step according to their *Switch On/Off* position. The five other articles (Xu *et al.*, 2009; Miller *et al.*, 2013; Bichraoui-Draper *et al.*, 2015; Lu and Hsu, 2017; Vasconcelos *et al.*, 2017) run an LCA calculation directly into their agent-based model and they do not use specific LCA software.

- A hybrid analysis has been used in 28% of the articles. For all these articles, the consumption system is modelled by ABM and the affected part of the LCA computational structure is the final demand vector. Attallah et al. (2014) use LCA to quantify the avoided impact at the project level (residential building) according to the selected credits of the certification that is targeted. Independently, ABM is run to evaluate the adoption rate of sustainability policies. Thus, LCA scores are aggregated according to the ABM results to obtain the total reduced impacts to the environment.

**Degree of coupling.** Regarding the degree of coupling, hard-coupling is used 22% of the time, against 67% for the soft-coupling as described Table 4. Tight-coupling has never been used, and the 11% remaining articles do not have any degree of coupling, since ABM and LCA are used in a complementary way.

Walzberg, Samson and Merveille (2018) used a hard-coupling to manage temporally disaggregated data of the electricity mix. At each hour of the day, they consider the impact associated with the on- or off-peak electricity mix, so their model requires a flow of data at each time step (running LCA calculation needs as inputs the dynamic state of the agent *Appliance*). Table 4 **Erreur ! Source du renvoi introuvable.** shows that every paper with a feedback



loop are hard-coupled. Data flow both ways, since LCA outputs are returned as an input for ABM, thereby requiring a high degree of coupling. Half of these hard-couplings are integrated, while the remaining half is hybrid. Notably, all studies that modelled technological agents used hard-coupling.

*Table 4 Repartition of the articles according to the presence of feedback and technology agents based on the classification of Table 2 and Figure 1. Percentages in italic are subtotals while figures in black are totals (e.g. 22% of the articles adopted a hard-coupling and, among them, half of the coupling type is hybrid)*

		Feedback		Technological agents		Type of coupling			N. m.
		Yes	No	Yes	No	Integration	Hybrid	Complementary	
Degree of coupling	Total %	<b>22%</b>	<b>78%</b>	<b>11%</b>	<b>89%</b>	<b>39%</b>	<b>28%</b>	<b>11%</b>	<b>22%</b>
Hard	<b>22%</b>	<i>100%</i>	<i>0%</i>	<i>50%</i>	<i>50%</i>	<i>50%</i>	<i>50%</i>	<i>0%</i>	<i>0%</i>
Tight	<b>0%</b>	<i>0%</i>	<i>0%</i>	<i>0%</i>	<i>0%</i>	<i>0%</i>	<i>0%</i>	<i>0%</i>	<i>0%</i>
Soft	<b>67%</b>	<i>0%</i>	<i>100%</i>	<i>0%</i>	<i>100%</i>	<i>36%</i>	<i>28%</i>	<i>0%</i>	<i>36%</i>
Complementary	<b>11%</b>	<i>0%</i>	<i>100%</i>	<i>0%</i>	<i>100%</i>	<i>0%</i>	<i>0%</i>	<i>100%</i>	<i>0%</i>

**Affected parts of the LCA computational structure.** In the corpus under study, the technosphere matrix and the final demand vector were the affected computational parts. The LCA computational part for the studies with a complementary approach is unaffected, since no data are exchanged. For 66% of the articles, ABM was used to model the consumption system and to compute the final demand vector. In every study with a temporal consideration based on future outcomes, except for one study that used a complementary approach, the final demand vector was affected by the coupling, which suggested that ABMs have been widely used to forecast market penetration. Eighty-five percent of the articles for which the final demand vector is affected are coupled softly. The other fifteen percent are hard-coupled with a feedback loop.

In (Davis, Nikolic and Dijkema, 2009; Wang, Brême and Moon, 2014a; Walzberg *et al.*, 2018), ABM was used to model part of the technosphere matrix, and for all of them, processes of the technosphere were modelled as agents. At each time step, the technosphere matrix can (a) shrink according to the processes that are or are not involved—in

a given moment (i.e., row and columns can be added or removed) and (b) be updated according to the interactions that the processes of the supply chain have with one another). (Davis, Nikolic and Dijkema, 2009; Walzberg *et al.*, 2018) integrated LCA in ABM in a hard-coupling way, whereas (Wang, Brême and Moon, 2014a) has a complementary approach in which the LCA technosphere matrix is shaped by another model. No mention of the temporal consideration of the study was given, which implies that the authors were interested in the dynamic of the interactions among agents of the supply chain instead of temporal dynamism.

### 3.3. Inventory

**LCA foreground/background data.** For most studies, inventories of the foreground LCA data were collected from ABM simulations. The ABM results were used to create the final demand vector. Elementary flows associated to the foreground data are obtained from existing LCA studies from literature in many studies (Xu *et al.*, 2009; Lu and Hsu, 2017; Onat *et al.*, 2017; Vasconcelos *et al.*, 2017). Vasconcelos *et al.* 2017 used an existing life cycle assessment to compute the quantity of air pollutant and greenhouse gases emissions for each kilometre travelled by car (functional unit). A total of 31% of the studies used the Ecoinvent life cycle inventory database (Weidema *et al.*, 2013) as background data, either imported in the ABM for integrated models (Davis, Nikolic and Dijkema, 2009; Walzberg *et al.*, 2018), which were run thanks to an LCA dedicated software for hybrid coupling or complementary use. Bustos-Turu *et al.* (2016) and Walzberg, Samson and Merveille (2018) used a disaggregated energy supply mix to account for the time-dependency of energy production. In both studies, the ABM generates at each time-step the electricity demand (foreground data) as well as the time-dependent electricity supply mix (background data). To this end, Walzberg, Samson and Merveille (2018) represent the Ontarian electricity mix as a network of technological agents exchanging different elementary flows according to the time of the day.

**ABM inputs.** ABMs can be complex and often require a considerable amount of socio-demographic or -economic data to set up the design of the agent's profile. Four studies (Navarrete Gutierrez *et al.* 2015; Lu & Hsu 2017; Hicks *et al.* 2015; Attallah 2014) are based on surveys that were previously elaborated by the research team. For example, Omar Attallah *et al.* (2014) designed and analysed statically survey questions to identify the different stakeholders and determine their attributes. In addition to data at the agent level, ABM also uses contextual data specific to the

environment. For example, (Walzberg *et al.*, 2018) used the national weather database to determine heating needs. Three studies (Heairet *et al.*, 2012; Lu and Hsu, 2017; Bustos-Turu *et al.* 2016) used spatialized information from geographic information system (GIS), a tool that represents and analyses spatial information. Three others (Bichraoui-Draper *et al.*, 2015; Miller *et al.*, 2013; Navarrete Gutierrez *et al.*,2015) evoke the possibility of adding GIS extension to directly model the map and to extract environmental parameters.

**Data exchange.** If the implementation of ABMs requires a massive collection of data, they produce a high quantity of data that can be useful for the LCA inventory at different life cycle stages as shown Figure 4. We identified in the corpus five main types of information generated by ABM. These ABM outputs were used to support the description of the use and manufacturing phase.

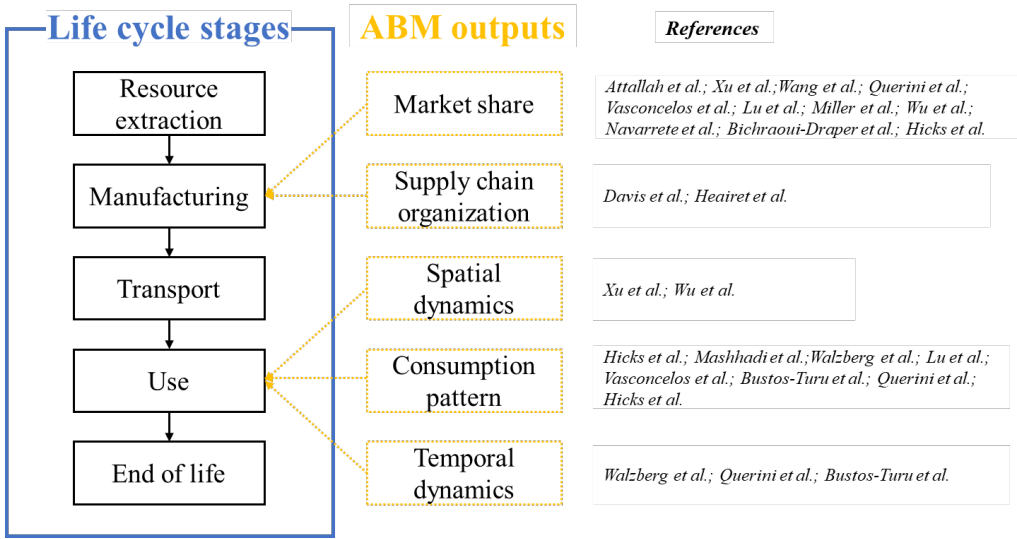


Figure 4 Data extracted from ABM at each life cycle stages in the articles of the corpus (except studies using ABM and LCA in a complementary use). References can appear several times according to the life cycle stages that are considered by the study.

In integrated models, every LCA calculations are computed directly in the ABM thanks to the importation of the necessary databases or parameters values. For studies with a hybrid approach, no information about the interconnection between both models is given, apart from (Navarrete Gutierrez *et al.*, 2015a) who use SysML for data-management. If an LCA software is used (e.g., Gabi and Simapro), a protocol must be created. In theory, the LCA practitioner can use any existing LCA software to perform the LCA, even if Navarrete Gutierrez *et al.* (2015)

highlight that the interaction between different software can be challenging to implement. In the other studies, ABM outputs were aggregated at the end of the simulation and then were feed manually into the LCA.

### 3.4. Impact assessment

**LCIA method.** Half of the environmental studies are multi-criteria, but most of them are only based on several indicators, mostly energy-related. For example, Bustos et al. (2016) use only climate change and particulate matter formation mid-point indicators from the ReCiPe method to run their multi-objective optimization. All of the articles using all of the ReCiPe mid-point indicators have a coupling hybrid type. Indeed, as proper LCA software is used, it eases the calculation step. None of the studied articles presents dynamic impact assessment methods. Indeed, ABM has not been used to simulate any environmental mechanism; thus, no characterization factors are temporally or spatially modified over time. (Susie Ruqun Wu *et al.*, 2017) were the only to mention a possible use of ABM to generate s dynamic LCIA stage in addition to its current use as input for LCI data.

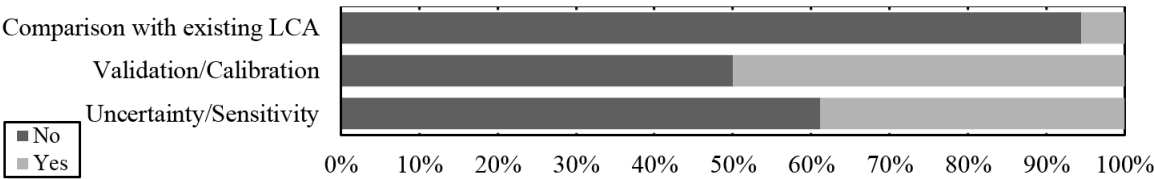
**ABM formalization.** The agent decision-making architecture is modelled based on probabilistic rules and decision trees in eight and three studies, respectively. In both cases, agents were considered to be stochastically reactive, since they do not elaborate plans. Agents can be qualified as pro-active in three studies: (Bustos-Turu *et al.*, 2016) to develop an activity-oriented architecture in which travellers' schedules adapt to various events and incentives, Walzberg, Samson and Merveille (2018) exploited the socio-psychological model from Kaiser et al. (2010) and Lu and Hsu (2017) model four cognitive processes (repetition, deliberation, imitation and social comparison). Half of the reviewed papers model a social network (neighbours or friends) from which arise interpersonal interactions that modify individual behaviours.

### 3.5. Interpretation

**LCA Uncertainty/Sensitivity Analysis.** No study refers to uncertainty analysis but more than 60% of the articles conducted a sensitivity analysis (Figure 5). Sensitivity analysis can be performed to determine (a) which parameters influence the outputs and (b) parameters' contribution to the variability of the outcomes. (Raihanian Mashhadi and

515 Behdad, 2017) carried out a sensitivity analysis that aimed to understand the influence of some input parameters  
 516 (environmental friendliness, perceived control, habit and network structure) on the overall results (goal (a)). Linear  
 517 correlations were found between each of these four parameters and the percentage of turned-off decisions. (Xu *et al.*  
 518 *et al.*, 2009) ran a sensitivity analysis with the (b) approach: they studied the contribution of the uncertainty associated  
 519 with the agent *Consumer's* parameters to the uncertainty of the overall model. To do so, the authors set  
 520 homogeneous consumers. It results in higher uncertainties than with the heterogeneous model, thereby  
 521 demonstrating that the real world needs a variety of consumer profiles to be correctly simulated.

522 The studies conducted the sensitivity analysis differently: (Wang, Brême and Moon, 2014b) used a design of  
 523 experiment, whereas (Bichraoui-Draper *et al.*, 2015) evaluated the sensitivity of inputs parameters based on a  
 524 correlation matrix of the exogenous variables and LCA results, which demonstrated the potential profit that farmers  
 525 are expected to make and has a direct impact on the LCA results. They applied the same methods for the farmers'  
 526 parameters. (Xu *et al.*, 2009) used a normal distribution for endogenous consumer's parameters (leadership power,  
 527 social needs, need satisfaction and uncertainty) instead of a uniform one and showed that these four parameters  
 528 slightly influence the outcomes.



530 *Figure 5 Repartition of the articles according to the three criteria related to the interpretation phase of LCA*

531 **ABM Validation/Calibration.** Six articles refer to ABM validation (Onat *et al.* 2017; Wang *et al.* 2014a), but only  
 532 four of them explain the procedure they established (Xu *et al.* 2009; Walzberg *et al.* 2018; Bichraoui-Draper *et al.*  
 533 2015; Lu & Hsu 2017). The major part of the corpus raises validation as a necessary step for model robustness.  
 534 Some mention it as a limit to their study (Susie Ruqun Wu *et al.*, 2017), while others aim to do so thanks to field  
 535 studies (Miller *et al.*, 2013; Raihanian Mashhadi and Behdad, 2017). (Xu *et al.*, 2009) used historical data to validate  
 536 their model in two steps: (1) checking if the e-commerce market share curve is fitting the current one and (2) running

537 of 1000 Monte-Carlo simulations. (Lu and Hsu, 2017) predicted a transport mode share in 2018 and validated their  
538 model with an official forecast data of China. (Bichraoui-Draper *et al.*, 2015) used a static and dynamic method to  
539 validate their model. The former one is similar to the one that is usually used by authors in the rest of the corpus  
540 (i.e., a comparison of the results with the observed data), while the latter one uses a multiple-linear regression model  
541 to test the fitness of their model. As the data were not available to date on switchgrass adoption, these researchers  
542 decided to validate their results with a different plant (genetically engineered soybeans) adoption in the U.S. The  
543 multiple-linear regression's goal is to determine which predictor variables are truly related to the response, and by  
544 doing so, it helps to validate the internal hypothesis. The researchers showed that their choice of independent  
545 variables was correct.

546 (Xu *et al.*, 2009) applied a statistical analysis to find the combination of parameters with which their model best fits  
547 the historical data of the U.S. market share from 1998-2005. However, they highlight the lack of available data with  
548 a technology that is too young to be well modelled and calibrated. (Lu and Hsu, 2017) used as well historical share  
549 data from 2003 to 2014 to fit the parameters of their model. (Vasconcelos *et al.*, 2017) used existing car fleet  
550 statistics to calibrate their model. Survey studies enable the model parameters to be adjusted to strengthen model  
551 robustness and use the results as forecasts.

552 **ABM Graphical Output.** Thirty-nine percent of the articles propose a graphic interface by which to visualize the  
553 ABM outputs. This graphical visualization can be rather elementary and illustrates, for example, the connections  
554 between the agents of the supply chain (Heairet *et al.*, 2012; Mashhadi and Behdad, 2017) or the rate of adoption  
555 (Pambudi, Dowaki and Adhiutama, 2016). This graphical output is also used by Miller *et al.* (2013) and Wu *et al.*  
556 (2017) to display the spatial evolution of the agents. Navarrete Gutierrez *et al.* (2015b) and Lu and Hsu (2017)  
557 created interfaces that contain a map and sliders or switch-on buttons to adjust the value of several parameters of  
558 the simulation.

559 **Comparison with conventional studies.** Wang, Brême and Moon (2014b) compared their result with an already  
560 existing company's report, and they demonstrated how results are strongly changed when introducing the market  
561 penetration of potential new products. Results between a conventional LCA study made by Nestlé and the hybrid

LCA were similar for bottled beverages but were profoundly different for tap water and aluminium bottles, which is explained qualitatively by uncertainties and the dynamic demand of the hybrid LCA. Wu *et al.* (2017) compare the life cycle sustainable results that were obtained with an ABM of green building development on a city scale with a predefined static policy scenario. Nonrenewable energy saved during the operational stage was 22% higher with the static policy scenario than with the incentive annual dynamic one.

567

The articles of the corpus have been compared against a set of criteria and the major results are summarized below:

-The coupling of ABM and LCA has been used so far in 18 case studies in different sectors: agriculture, transport, daily products and construction.

-In most cases, ABM has been coupled to LCA in order to model foreground systems with too many uncertainties arising from a behaviour-driven use phase, local variabilities, emerging technologies.

-Both attributional and consequential modelling methodologies have been used, but CLCA has been applied in most cases

-Foreground inventory data have been mainly collected from ABM at the use phase

-ABMs have never been used for modelling the impact assessment phase

577

## 4. Discussions

### 4.1. Theoretical opportunity: How can the ABM enhance LCA?

In light of the results of the review, several points have been identified for which ABM&LCA coupling may enhance LCA for some of its methodological weaknesses. Table 5 summarizes how the use of ABM may improve LCA in each of its methodological phases, either for the consequential approach or for both modelling methodologies. The following sections describe each contribution.

584 Table 5 Potential contribution of ABM through the different LCA phases (MM stands for modelling methodology)

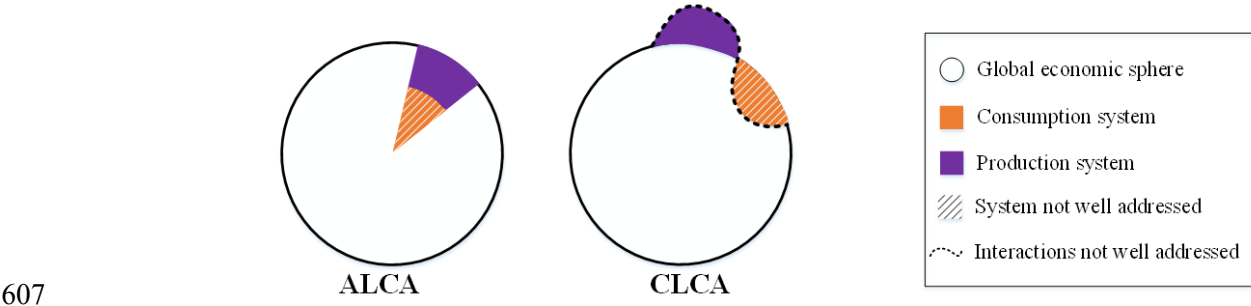
LCA phases		ABM support to LCA	Enhanced knowledge from ABM	MM
Goal and scope	Scenario	Explore usage scenario	Consumption system	ALCA and CLCA
	System boundaries	Identify system expansion	Consumption and production interaction	CLCA
LCI	Foreground data	Collect use phase precise data	Consumption system	ALCA and CLCA
LCIA	LCIA methods	Bring temporal and spatial	Environmental system	ALCA and CLCA
		dynamics		
Interpretation		Visualize graphically	--	--
		Identify targeted guidelines	--	--

585 **Goal and scope.** As previously highlighted, ABM has been extensively used to explore different LCA scenarios.  
586 Thanks to the forecasting capacity of ABM, coupling both tools represent solutions for exploring the effectiveness  
587 of different sustainable policy implementation scenario (e.g., taxes and incentive regulation). ABM can also be used  
588 to cluster users' behaviours as a function of the typologies of use, for example. Scenarios can be associated with  
589 these users' archetypes to assess the panel of possible LCA scores of a product system.

590 The main modelling challenge for CLCA is double: (i) to spot changes in demand (rebound effect, behaviour shift)  
591 or extension to other products (alternative use of constrained production factors, market effect, competing products),  
592 and (ii) to evaluate to what extent these changes in the consumption system impact the production system. Modelling  
593 the life cycle product with the consequential methodology turns out to be a tough task, because the interaction  
594 between the consumption and the production system (represented by the dotted line in Figure 11) is not well  
595 apprehended yet. LCA is not a tool to consider the complexity of the mechanisms of product/technology adoption,  
596 which depends to a large extent on the perception of the new product/technology and its acceptance (i.e., the  
597 consumption sphere). Economic models have been increasingly used to describe the link between consumption and  
598 production systems. However, these top-down models represent humans as purely rational, which is a limitation  
599 that was identified by Yang and Heijungs (2017); as already mentioned above, the introduction of behavioural  
600 science could be useful to complement this economic approach according to (Miller and Keoleian, 2015). ABM has  
601 already been used in industrial and process engineering research to model supply chains (see Shen *et al.* (2006) for



602 a comprehensive review). ABM can supplement LCA to investigate how consumers are going to react to emerging  
 603 technologies or the new product development (e.g., acceptance, rejection, and spill-over effects) and how this  
 604 answer, in turn, affects the whole supply chain. Thus, ABM is a relevant tool with which the LCA practitioner can  
 605 quantify the potential effects over time that the product system introduces in the foreground and background  
 606 systems.



608 *Figure 6 Representation of the enhanced dimensions thanks to ABM for attributional LCA and consequential LCA, in compliance with the*  
 609 *description of Weidema et al. (1998) of both modelling methodologies*

610 **Inventory.** The ways in which users interact with products may profoundly affect the results of environmental  
 611 studies, and products with an impacting use phase (e.g., housing, cars, and appliances) need quality inventory data.  
 612 (Langevin, Wen and Gurian, 2015) highlighted the need to consider inter-individual behavioural variation when  
 613 modelling the use phase instead of simple averages. To this end, the benefit to supplement LCA studies with  
 614 behavioural science was pointed out by Polizzi di Sorrentino et al. (2016). Introducing socio-cultural, -demographic  
 615 and –economic factors is a valuable method to simulate different usage patterns and to obtain the range of possible  
 616 outcomes due to behavioural differences. Thanks to the ability of ABMs to represent individuals with high cognitive  
 617 capacities, they allow a better understanding of the increasingly complex consumption system, which is not well  
 618 described in current life cycle studies (represented by the orange hatched area in Figure 11). Use phase description  
 619 can gain precision through the collection of inventory data from ABM outputs. Within the reviewed papers, two  
 620 studies take advantage of the dynamic data that are generated by the ABM to assess the electricity environmental  
 621 impact hour by hour. This approach allows for the primary energy source proportion to be accounted for at the  
 622 moment when the electricity is demanded. This adjustment is particularly relevant for energy-intensive product

623 systems (e.g., the use phase of residential buildings and plug-in electric vehicles) whose electricity demand is highly  
624 time-dependent. ABM could be a useful tool to output time-dependent data instead of averaged data.

625 In the same way as for dynamic temporal data, ABM can generate spatially distributed data that can be useful to  
626 investigate localized environmental impacts that are dependent on spatial dynamics. For example, Miller et al.  
627 (2013) explained the high dependence of switchgrass environmental impacts on previous land uses, since there was  
628 an initial sediment emission and a spike in nutrients when the former land was unmanaged. In some cases, the LCA  
629 results can be different spatially according to social adoption and the usage pattern as demonstrated by Wu et al.  
630 (2017). Spatial information that is obtained with an ABM could be useful to assess, for example, to what extent the  
631 economy of scale can impact LCA scores or to identify targeted policy incentives according to the area (e.g., rural  
632 versus urban areas).

633

634 **Impact assessment.** To date, the temporal course of emissions is undefined in LCIA, and environmental systems  
635 are considered through steady-state modelling (Shimako, 2016). Recent studies have moved towards dynamic LCA  
636 to address the inconsistency of the temporal assessment (Beloin-Saint-Pierre, Heijungs and Blanc, 2014). While the  
637 articles of the corpus all used ABM data as input for a robust LCI description, the spatially and temporally  
638 distributed data that were obtained thanks to the ABM can also be used during the LCIA step to simulate dynamic  
639 environmental mechanisms and, in this way, to improve environmental systems modelling. It would be particularly  
640 relevant to improve both human exposure and short-term indoor chemical fate in LCA in so far as behaviour-related  
641 factors profoundly influence chemical fates and exposure probabilities. For example, indoor pollutants do not have  
642 the same residential time indoors based on occupant ventilation strategies. Occupants are exposed to indoor  
643 chemicals through near-field exposure pathways that are highly behaviour-driven: for example, the intake of indoor  
644 chemicals via inhalation depends on the fraction of time spend at home (Jolliet *et al.*, 2015). In return, these human  
645 intakes affect the indoor fate of chemicals significantly (Zhang, Arnot and Wania, 2014). This approach implies a  
646 substantial focus on (i) the heterogeneity in human profiles and activities that are key drivers for quantifying the

dynamic of air emissions and the resulting human exposure in indoor environments and (ii) the short-term dynamics of chemical emissions and exposure.

**Interpretation.** As explained by Kelly et al. (2013), environmental policies cannot be put into place effectively without holistic modelling of complex systems and the dynamic interactions that take place among the numerous stakeholders. Simulation of socio-economic or socio-ecological factors that drive interactions among entities (humans, institutions, etc) allows for the impacts and outcomes to be explored at the system level. ABM can help in understanding the main factors that influence agent's decision-making process, how the adoption pattern affects the environmental impact of the system, and from this, which policies can help support more sustainable systems. At the product level, ABM can help LCA to identify the design with which users behave more sustainably. Inversely, it can help to identify behaviours that positively or negatively affect the environmental performance of a system and support the development of targeted environmental guidance or policies. An ABM graphic representation can then be a strategic point to help decision-makers better comprehend the model and communicate results.

#### 4.2. Recent LCA developments for which ABM could be relevant

In this section, we specifically identified three recent developments in the LCA field for which the use of ABM could be beneficial both at the inventory and impact assessment phase.

**Regionalization.** Regionalized LCA increase the results accuracy by considering site-specific conditions (Hellweg and Milà i Canals, 2014). However, in practice, regionalization in LCA studies is rarely performed (Mutal and Hellweg, 2009) because the acquisition of spatial data is challenging. To ease this step, GIS has been integrated in the inventory and impact assessment modelling (Geyer *et al.*, 2010; Mutel, Pfister and Hellweg, 2012; Liu *et al.*, 2014) and the open source Brightway software (Brightway2, 2016) includes GIS capabilities in the LCA calculation. In the same way, the integration of the spatial analysis capabilities of GIS within the ABM could support the LCIA

671 of product systems exhibiting spatial dynamics and could help the regionalization of both the inventory and impact  
672 assessment phases. In ABM, agents are often linked to each other by spatial relationships and are situated in an  
673 environment that constrains their actions. For example, an agent “pedestrian” is spatially linked to the agent  
674 “building” when the pedestrian is inside the building, and its path is constrained by the agent “road” when it tries  
675 to reach the agent “building”. GIS provides geospatial details that are based on actual geographic locations. The  
676 integration of GIS within ABM helps to analyse physical factors such as accessibility, distances and to generate a  
677 3D graphical environment. Therefore, there is a growing interest in the integration of GIS within ABM, and  
678 nowadays, many models have already coupled both tools (Brown *et al.*, 2005).

679 **Dissipative use.** The current nature of the LCA fails to address the major issue of the dissipative use generated by  
680 human activities at the use or end-of-life phase of the product system. The environmental impact of plastic pollution  
681 in the ocean is recognized as one of the most serious issues affecting the marine environment. Marine debris mainly  
682 result from throwing product packaging into the environment, but LCA lacks models to assess the source, quantity  
683 and transport of those types of plastics. ABM could support LCA in integrating behaviour-driven dissipative uses  
684 at both the inventory and impact assessment phases.

685 **Indoor pollution.** The agent-based approach has a high potential to support the impact assessment phase with  
686 dynamic behaviour-related models, and this could also be relevant to estimate the human health impacts in indoor  
687 environments across the product systems life cycle. As highlighted by (Hellweg *et al.*, 2009), health effects from  
688 indoor pollution at the manufacturing and the use phase should be included in LCA.

689 Engineered nanomaterials have been increasingly used in many sectors, although they present potential effects to  
690 the environment and human health (Vance *et al.*, 2015). The behaviour of engineered nanomaterials in indoor  
691 environments is concentration dependent and driven by dynamic mechanisms that existing steady-state LCIA  
692 models fail to describe. To evaluate the human health hazards posed by engineered nanomaterials at the  
693 manufacturing phase, Tsang *et al.* (2017) have developed a dynamic model as well as exposure scenarios to model  
694 different situations of nanomaterial handling in a workplace. To go one step further, these LCIA exposure models

695 could be refined according to users' archetypes based on behaviour-related aspects (working time, preventive  
696 measures in the production phase) generated by an ABM.

697 Besides, the life cycle of products used indoors only consider the emissions occurring during production and  
698 disposal phases and neglect the use phase impacts from exposure to chemicals that have been released in the indoor  
699 environment. The indoor residence time of these chemicals is significantly affected by physical removals from  
700 occupants activities such as windows opening. Occupants are exposed to indoor chemicals through near-field  
701 exposure pathways that are highly behaviour-driven, and physiological-dependent (Fantke *et al.*, 2016) and these  
702 human intakes affect significantly the indoor fate of chemicals (Zhang, Arnot and Wania, 2014). Therefore, there  
703 is a need to address the use phase impact of chemicals from products used indoors with a substantial focus on the  
704 heterogeneity in human profiles and activities which are key drivers for quantifying the dynamic of air emissions  
705 and the resulting human exposure in indoor environments. The agent-based approach would be particularly well  
706 suited to capture the variability of lifestyle-induce indoor exposure.

707

#### 708 **4.3. Methodological issues: how can the coupling be done?**

709 The way that both tools are coupled depends on the expected consistency and flexibility. Integrating LCA with  
710 ABM leads to a consistent, unique model, but models are highly dependent, since the ABM architecture is embedded  
711 in the LCA data structure. The main drawback lies in the difficulty in developing an integrated model, since the  
712 modeler must have expertise in both computer science and environmental engineering fields. However, integration  
713 is highly recommended when ABM is embedded in LCA, i.e., when ABM does not represent the whole system but  
714 models a process (already existing or not in LCA) that interacts with other LCA processes within this system. Thus,  
715 ABM and LCA integration is relevant when the dynamic effects in a matrix system of the LCA computational  
716 structure is partly modelled by ABM, i.e., when ABM is used to model environmental and/or production system  
717 (impacting the characterization and the technosphere matrix, respectively, according to Figure 2).

718 The hybrid analysis offers a good trade-off between both aspects (consistency and flexibility), since models  
719 exchange data externally through parameters while keeping them independent from one another; thus, the  
720 parameters can be adjusted without impacting the other parameters. Hybrid uses are therefore particularly well-  
721 suited for studies in which the ABM generates stand-alone processes. Quantities that will be further used in LCA  
722 computation are the only data exchange that is required between the two models. This is the case when agents are  
723 intended to represent the consumption system (only influencing the final demand vector, as shown in Figure 2).

724 The degree of coupling profoundly influences the computational time, as well as the programming time. Hard-  
725 coupling is meaningful when studies aim to integrate feedback on the environmental impact of the product in the  
726 adaptive decision-making process or the self-learning mechanism of some agents. (Baustert and Benetto, 2017)  
727 emphasize the promising approach of hard-coupling (called LCA/ABM symbiosis by the authors) for feedback  
728 information of the agents to integrate a green consciousness. Agents can adjust their behaviour at each time step  
729 based on informed choices.

730 Tight-coupling is useful when ABM outputs should be assessed at each time step. This is the case when modelling  
731 non-linear relationships (for example, a dose-response of the human body) or by using data changing over time  
732 instead of average one (for example, the electricity mix). When none of these conditions is required, ABM outputs  
733 can be aggregated at the end of the simulation, and soft-coupling is preferred. Indeed, it limits the computational  
734 time, since data are exchanged only once.

735 The following guidance diagram (Figure 7) aims to accompany the LCA practitioner through the coupling  
736 possibilities for both the type (hybrid analysis or models integration) and the degree (soft, tight or hard) as defined  
737 in the previous section. Other combinations than the ones presented are possible; we hereby present what we  
738 consider to be an adequate solution regarding the relevance and flexibility).

739 The type of coupling depends on the system the LCA practitioner aims at enhancing with ABM (i.e., the production,  
740 consumption or environmental system). The degree of coupling depends on the modelling choices that the LCA  
741 practitioner makes according to several yes/no options that arise all along the LCA phases. If a feedback loop is

necessary, then hard-coupling should be set up. If not, tight-coupling can be put into place if the LCI data are time-dependent or if the LCIA relationships are nonlinear.

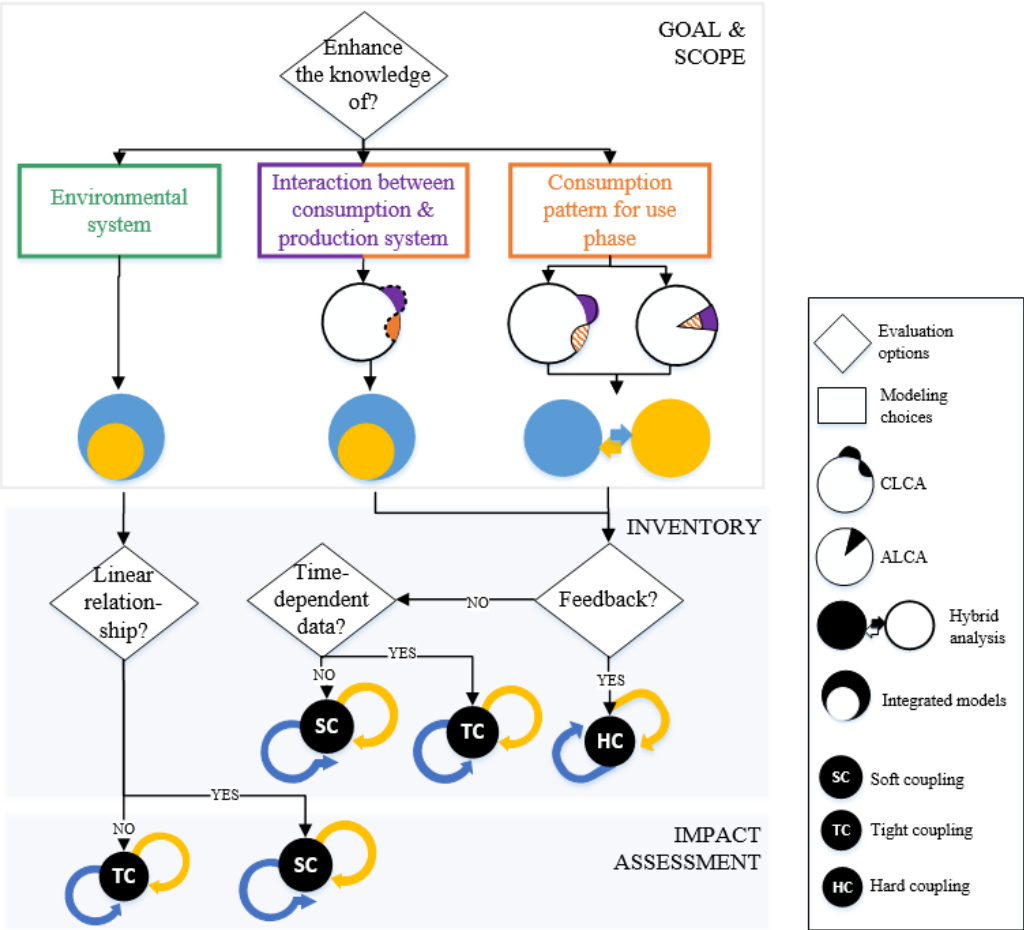


Figure 7 Guidance diagram for possible options of ABM and LCA coupling at different LCA phases, as proposed by ISO 14040 and 14044, concerning the type of coupling as defined Table 2 and the degree of coupling as defined Figure 1

#### 4.4. Limitations and perspectives of the coupling methodology

Based on the theoretical and methodological issues, we have identified several questions associated with the coupling of ABM and LCA. In this section, we discuss the most relevant limitations in the coupling methodology and implementation and how they could be further addressed.

Coupling ABM with LCA requires expertise in both scientific domains. If integration of LCA in ABM is preferred, the LCA practitioner may know that the LCA computational structure defines agents as part of the life cycle inventory. The hybrid approach requires both models to be linked so that the exchanged parameters can flow from

754 one model to another. However, as highlighted by (Marvuglia *et al.*, 2016), ABM suffers from the difficulties that  
755 are linked to its implementation. LCA current tools have limited functionalities to support interaction with other  
756 software, thus resulting in difficulties in directly calling these latter from a simulator.

757 The reviewed papers propose a rather simplistic decision process, and several papers highlight that their utility in  
758 guiding any real policymaking is constrained by their simplicity (Susie Ruqun Wu *et al.*, 2017). Implementation  
759 difficulties of ABMs could be avoided due to existing dedicated platforms, such as Netlogo (Gaudou *et al.*, 2017),  
760 Anylogic (Anylogic 4.0, User Manual), and GAMA (Grignard *et al.*, 2013), which already integrates complex  
761 cognitive architectures, such as the Belief-Desire-Intention (Caillou *et al.*, 2017). Such platforms ease model  
762 development with an explicit and natural representation of human behaviour, which allows non-computer scientists  
763 to be included in the modelling process. Thus, decision-makers can be involved from the early modelling stages  
764 and, as underlined by (Marvuglia *et al.*, 2018), the transparency of these participatory modelling processes favour  
765 the acceptance of the final decision by different stakeholders. Besides, these platforms are continuously upgraded,  
766 and one could imagine that they could later automatically integrate the LCA data, as some already do with GIS for  
767 example (e.g., GAMA).

768 The use of GIS data, as well as national databases as inputs to the agent-based model, generates highly context-  
769 specific LCA studies. This enables to account for the specificities of different countries and further identify targeted  
770 policies; however, this also prevents the results from extrapolating to other situations or from using the model in  
771 another context.

772 ABM brings other sources of uncertainties that must be accounted for to present reliable LCA results and increase  
773 the acceptance of ABM in the LCA field. The additional data collected to implement the ABM increases the  
774 uncertainty. On the other hand, one of the main sources of uncertainty in LCA comes from the choices and lack of  
775 knowledge of the studied system (*LCA in theory and practice* , 2018). The use of ABMs, allowing to evaluate  
776 different scenarios and account for the local variabilities of the foreground system, could be a solution to deal with  
777 this systemic uncertainty. For example, the prospective development of emerging technologies and the consumers'  
778 behaviour during the use phase of drinks, for example, are associated with many uncertainties; and Miller *et al.*



779 (2012) and Mashhadi and Behdad (2017) respectively tackle these uncertainties during the inventory phase with an  
780 ABM. Besides, (Wang *et al.*, 2014) argue that uncertainties in the decision process in traditional LCA studies could  
781 be addressed with ABM. Nevertheless, the evaluation of uncertainties in ABM and LCA coupled models is  
782 challenging. To tackle this issue, (Baustert and Benetto, 2017) propose a framework to spot the uncertainty sources  
783 and choose the appropriate propagation methods. In their review, they identify four sources of uncertainties that  
784 could apply to ABM & LCA coupled models: parameters uncertainty, uncertainty due to choices, structural  
785 uncertainty and systemic variability. The different uncertainty propagation methods commonly used in both fields  
786 are compared against three criteria: applicability, accuracy and computational effort. Another important issue which  
787 hinders the acceptance of ABM in the field of LCA comes from the difficulties in validating the model, either  
788 because of the complexity and time-consuming aspects of the cognitive models that are involved or because of the  
789 lack of experimental data to compare them with.

790 Finally, in this article, we have only dealt with articles using ABM to enhance LCA. However, LCA could be used  
791 to enhance ABM (Marvuglia *et al.* refer to it as LCA-enhanced ABM). Several articles of the corpus use  
792 environmental awareness as an attribute that is defined rather simplistically (yes/no, low/medium/high). LCA could  
793 be used to refine the environmental awareness attribute in the decision-making process of ABMs, or define the costs  
794 related to environmental improvement in competition models to compare the market share of eco-friendly products  
795 between manufacturers (Liu, Anderson and Cruz, 2012). Furthermore, LCA gives new insight into the  
796 comprehension of complex systems, while the implementation of an ABM requires a massive amount of parameters  
797 to set up the environment in which agents evolve. Davis, Nikolic and Dijkema (2009) were the first to highlight that  
798 the use of LCA databases can ease the creation of a complex technological environment in ABM. An interesting  
799 research approach would be to transform every unit process from an existing LCA database into agents and to assign  
800 them interactions with each other according to the flows that are quantified in the database. The environmental  
801 impact that is associated with the response of the production system to the consumption demand could be assessed  
802 this way.

803

## 5. Conclusions

This paper reviews how and why agent-based modelling has been used to support life cycle assessment in the literature. It shows that to date, ABM has been mostly used to model usage patterns and their associated behavioural heterogeneity. ABM has also shown its worth in supporting system modelling for consequential LCA by forecasting the interaction between the production and consumption system (i.e., the reaction of the supply chain to the market demand according to product adoption rate for example). Finally, ABM has been used for its exploring capacity to simulate various scenarios.

We identified the methodological challenges that can be tackled by ABM at each LCA phase: (1) to draw up proper scenario in the goal&scope phase, (2) to collect foreground inventory data at any stage of the product system life cycle, (3) to address temporal and/or spatial dynamics that are driven by behavioural factors at the impact assessment phase, and (4) to support data interpretation and communication thanks to graphic representations.

This review establishes guidance on how to conduct the coupling according to the methodological choices that are made by the LCA practitioner. The type of coupling mostly depends on the computational part of the LCA that is modelled by ABM, i.e., which dimension the LCA practitioner wants to enhance by using ABM. The degree of coupling depends on three evaluation options: the time-dependency of data, the linearity of the relationships at stake and the presence of a feedback loop.

This theoretical analysis paves the way for future empirical case studies, and it would be valuable to confront the consistency of the theoretical interpretation with the results. Finally, we identified future research opportunities for the integration of ABM with LCA, which include regionalization, dissipative use and indoor air pollution.

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