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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

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

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

75 ABM has recently attracted attention as a complementary tool to LCA to model human behaviour and predict how
76 the dynamics of a system can be affected by internal or external factors. Davis, Nikolić and Gerard P.J. Dijkema
77 (2009) were the first to introduce the coupling of ABM with LCA to evaluate the sustainability of an emerging

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

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

94

95 **2. Materials and Methods**

96 **2.1. Selection of articles**

97 This review intends to collect papers in which ABM and LCA have been coupled. A focus is carried out on all
98 papers presenting a case study or a proof of concept in order to be able to analyse how the coupling was carried out
99 from a methodological point of view. Since this concern is relatively new, no temporal restriction has been applied.
100 The exhaustive search was performed with international bibliographic databases, Scopus, ISI Web Science, Science
101 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.

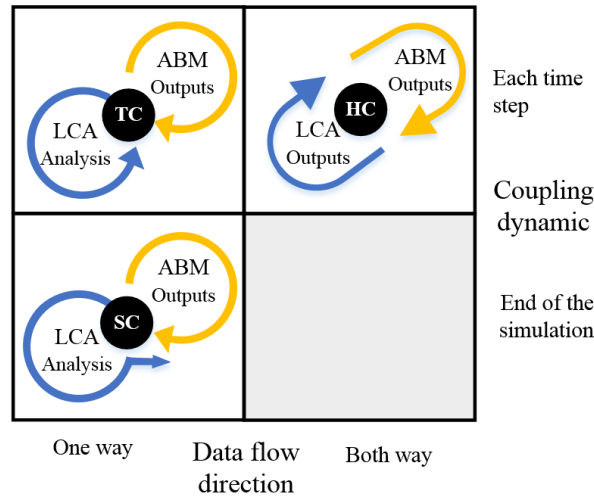
145 **Type of coupling.** The way in which ABM and LCA are coupled is referred to as the *type of coupling*, and it is
 146 examined to understand the internal working of each model, such as if a data flow is exchanged between both
 147 models or if both models are embedded in one another. We define 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

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

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

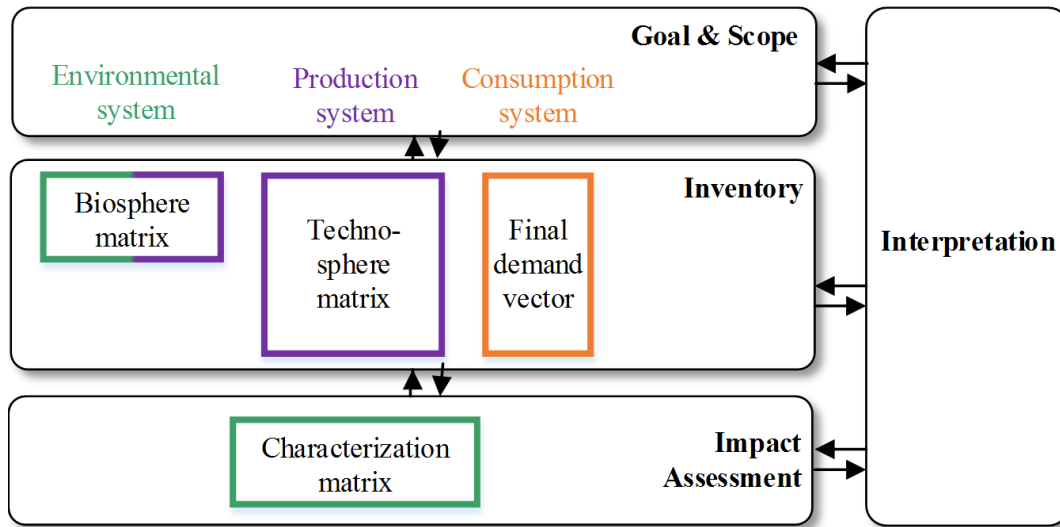


166 .

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)*

169 **Affected parts of the LCA computational structure.** Within the context of LCA, ABM can be used to simulate
 170 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 *x*)*

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**

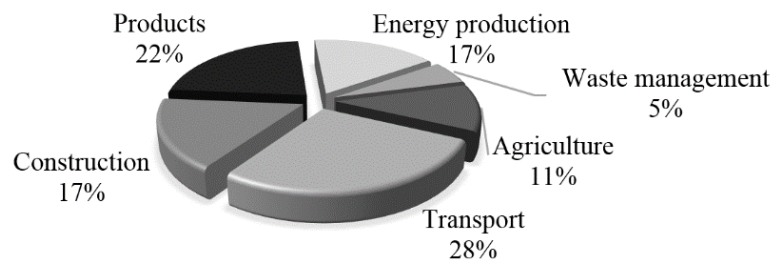
242 In total, 31 articles dealing with ABM and LCA were found according to the procedure detailed in the material and
243 method section, as shown in Figure S1 (Supplementary Information), and the exhaustive list can be found in Table
244 S1(Supplementary Information). The thirteen articles detailed 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.

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

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



278 *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
Walzberg et al., 2018	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
Vasconcelosa et al., 2017	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)
Mashhadi et al., 2017	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
Lu et al., 2017	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
Onat et al., 2017	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
Wu et al., 2017	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

Pambudi et al., 2016	Plastic waste	Appropriate strategies of recycling through environmental and social aspects	end of life	no	no	attributional	to integrate irrational decisions	Consumers	Willingness to change	not mentioned	not mentioned
Bustos-Turu et al., 2015	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
Bichraoui-Draper et al., 2015	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
Navarrete Gutiérrez et al., 2015	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
Querini et al., 2015	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
Hicks et al., 2015	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

Wang et al., 2014	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
Attallah et al., 2014	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
Miller et al., 2013	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
Heairet et al., 2012	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
Davis et al., 2009	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
Xu et al., 2015	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

284 **3.2. Goal and scope**

285 **LCA Goal.** We can identify three different types of goals. (i) Forty-four percent of the papers aimed to help
286 decision-making for sustainable policy implementation. For example, Lu and Hsu (2017) investigated different
287 incentives-based scenarios for the implementation of the high-speed railway Guangzhou-Shenzhen-Hong Kong in
288 2020: they first assessed the ticket fare that would result in the lowest environmental impact of the high-speed train,
289 and second, they proposed a scenario without through train with which the greenhouse gases emissions were
290 reduced by 25%. (ii) Twenty-two percent of the studies aimed to better describe the use phase. Since the
291 environmental impact of electrical appliances highly depends on the consumption pattern (e.g., time of use and
292 power management after usage), Mashhadi and Behdad (2017) propose an ABM to simulate consumption patterns
293 according to different user typologies and to further quantify the variability of the resulting LCA. (iii) The last 28%
294 of articles explores how emerging technologies could impact the environment by analysing how their supply chain
295 and market penetration would potentially develop. Heairet et al. (2012) studied the environmental impact of the
296 developing bioenergy industry due to an ABM that models each actor in the supply chain: the farmers for
297 switchgrass biofuel production, biofuel refineries and electric generators for the bioelectricity market.

298 Three studies model rebound effects (Xu *et al.*, 2009; Hicks, Theis and Zellner, 2015a; Walzberg *et al.*, 2018).
299 Walzberg, Samson and Merveille (2018) model both the direct and indirect rebound effect that can occur in smart
300 homes. They use an ABM to compute at each time step the monetary savings that result from the consumption
301 pattern of each household and further exploit the Canadian Input-Output tables to reallocate these savings in other
302 economic sectors. The authors quantify that the indirect rebound effect increases 24% of the use phase impact on
303 climate change. Hicks, Theis and Zellner (2015b) use the ABM to assess the increase in electricity consumption
304 (direct rebound effect) that results from the adoption of energy-efficient lighting technologies. These researchers
305 account for different agent typologies (as a function of preference, misinformation) and several policies. Xu et al.
306 (2009) use ABM to simulate the dynamics of the book market following the introduction of a self-pick-up option.
307 The authors evaluate the direct rebound effect on transport resulting from the purchase of e-books instead of
308 conventional books. The agent-based approach allows the authors to model the rebound effect as a function of the

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

311 **LCA Scope.** Half of the studied articles have a predictive approach and forecast possible outcomes with a time
312 horizon to 2020 for five articles (Xu *et al.*, 2009; Miller *et al.*, 2013; Bichraoui-Draper *et al.*, 2015; Florent and
313 Enrico, 2015; Navarrete Gutierrez *et al.*, 2015a). Hicks et al. (2015) forecast potential environmental impact savings
314 from the shift to efficient lighting technologies (compact fluorescent lamp and light-emitting diode) until the year
315 2083, which represents the most extended forecasting period of the corpus.

316 Regarding the life cycle steps considered, one-third of the studies only consider the use phase of the product system,
317 either because previous LCAs have shown that the use phase of the product system is the most impactful phase
318 (Attallah, 2014; Onat *et al.*, 2017; Vasconcelos *et al.*, 2017), or because the study aims to quantify the environmental
319 impacts that are associated with the heterogeneity of the consumption/usage pattern (Hicks, Theis and Zellner,
320 2015b; Raihanian Mashhadi and Behdad, 2017; Walzberg *et al.*, 2018).

321 Half of the corpus uses a consequential modelling methodology, among which two studies specify that both
322 attributional and consequential methodologies can be used (Raihanian Mashhadi & Behdad 2017; Miller et al.
323 2013), and seven studies do not specify the modelling methodology (Xu *et al.*, 2009; Navarrete Gutierrez *et al.*,
324 2015a; Querini and Benetto, 2015; Bustos-Turu *et al.*, 2016; Lu and Hsu, 2017; Vasconcelos *et al.*, 2017; Walzberg
325 *et al.*, 2018). We classified their modelling methodology as consequential, since ABM is used to investigate the
326 change of demand for products that are not in the system boundary of the product system under study. Therefore,
327 the product system is not isolated from the rest of the economy. For example, Lu et al. (2017) studied the
328 environmental impacts of the introduction of a high-speed railway, and the authors use ABM to quantify to what
329 extent this transportation mode displaced the other modes. These CLCAs only consider the consequences of the
330 introduction of an innovative product/emerging technology on its market share. ABM is used to assess direct
331 consequences on the foreground consumption system. Indirect changes in the activities all along the supply chain
332 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

358 defined by social (age, education, risk aversion, familiarity) and economic (potential profit) attributes. However,
359 the small correlations (<0.20) between the social factors and the CO₂ emissions during the growth of the crops,
360 ethanol generation, electric generation and ethanol distribution processes show that individual attributes have little
361 influence on the LCA scores, contrary to the economic factor *potential profit* (correlation of 0.67).

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

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

377 One of the key specificities of ABMs is the high number of agents that can be simulated. Vasconcelos *et al.* (2017)
378 simulate as many travellers as inhabitants in Lisbon, which are 547733. The number of agents, as well as their
379 attributes, can be static or evolve during a simulation. For example, the number of agents as *Developers* in Wu's
380 agent-based model is a function of the *Public* agents' environmental awareness, which is an attribute that evolves
381 at each time step. For agents with the most advanced cognition, the decision-making process is driven by the
382 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 CO₂ 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

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

411 - LCA and ABM are integrated in seven studies. Davis, Nikolic and Gerard P.J. Dijkema (2009) were the first to
412 extend LCA with ABM: in their model, the static LCA database can be considered as a *WorldMarket* agent
413 with which the other *Technological* agents can interact. The same procedure was used by Walzberg et al. (2018).
414 The authors represented some of the system processes from the LCA database ecoinvent 3.1, such as *Appliances*
415 agents evolving at each time step according to their *Switch On/Off* position. The five other articles (Xu *et al.*,
416 2009; Miller *et al.*, 2013; Bichraoui-Draper *et al.*, 2015; Lu and Hsu, 2017; Vasconcelos *et al.*, 2017) run an
417 LCA calculation directly into their agent-based model and they do not use specific LCA software.

418 - A hybrid analysis has been used in 28% of the articles. For all these articles, the consumption system is modelled
419 by ABM and the affected part of the LCA computational structure is the final demand vector. Attallah et al.
420 (2014) use LCA to quantify the avoided impact at the project level (residential building) according to the
421 selected credits of the certification that is targeted. Independently, ABM is run to evaluate the adoption rate of
422 sustainability policies. Thus, LCA scores are aggregated according to the ABM results to obtain the total
423 reduced impacts to the environment.

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

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

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

434 *Table 4 Repartition of the articles according to the presence of feedback and technology agents based on the classification of Table 2 and*
 435 *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*
 436 *them, half of the coupling type is hybrid)*

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

437

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

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

449 a given moment (i.e., row and columns can be added or removed) and (b) be updated according to the interactions
450 that the processes of the supply chain have with one another). (Davis, Nikolic and Dijkema, 2009; Walzberg *et al.*,
451 2018) integrated LCA in ABM in a hard-coupling way, whereas (Wang, Brême and Moon, 2014a) has a
452 complementary approach in which the LCA technosphere matrix is shaped by another model. No mention of the
453 temporal consideration of the study was given, which implies that the authors were interested in the dynamic of the
454 interactions among agents of the supply chain instead of temporal dynamism.

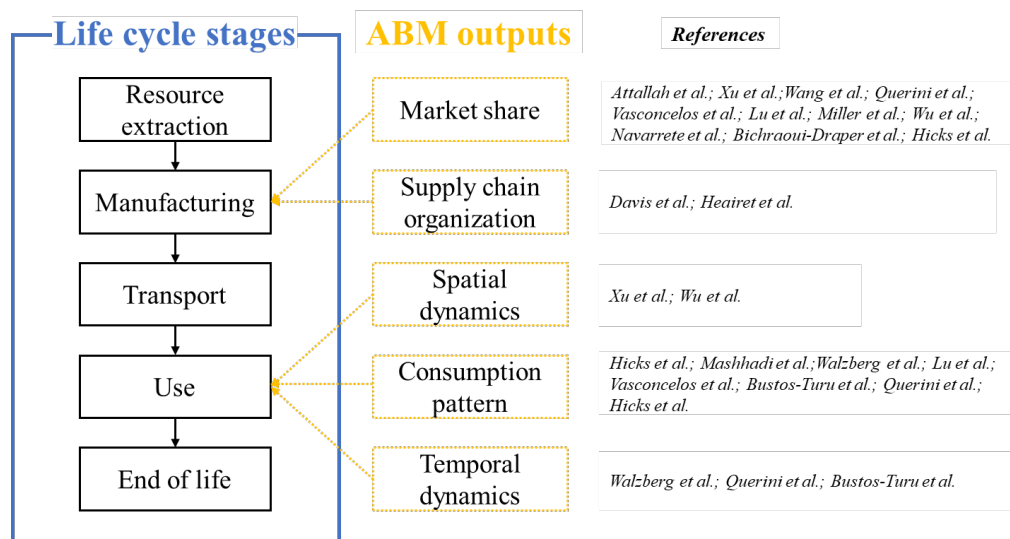
455 **3.3. Inventory**

456 **LCA foreground/background data.** For most studies, inventories of the foreground LCA data were collected from
457 ABM simulations. The ABM results were used to create the final demand vector. Elementary flows associated to
458 the foreground data are obtained from existing LCA studies from literature in many studies (Xu *et al.*, 2009; Lu and
459 Hsu, 2017; Onat *et al.*, 2017; Vasconcelos *et al.*, 2017). Vasconcelos *et al.* 2017 used an existing life cycle
460 assessment to compute the quantity of air pollutant and greenhouse gases emissions for each kilometre travelled by
461 car (functional unit). A total of 31% of the studies used the Ecoinvent life cycle inventory database (Weidema *et*
462 *al.*, 2013) as background data, either imported in the ABM for integrated models (Davis, Nikolic and Dijkema,
463 2009; Walzberg *et al.*, 2018), which were run thanks to an LCA dedicated software for hybrid coupling or
464 complementary use. Bustos-Turu *et al.* (2016) and Walzberg, Samson and Merveille (2018) used a disaggregated
465 energy supply mix to account for the time-dependency of energy production. In both studies, the ABM generates at
466 each time-step the electricity demand (foreground data) as well as the time-dependent electricity supply mix
467 (background data). To this end, Walzberg, Samson and Merveille (2018) represent the Ontarian electricity mix as
468 a network of technological agents exchanging different elementary flows according to the time of the day.

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

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

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



483

484 *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*
 485 *complementary use). References can appear several times according to the life cycle stages that are considered by the study.*

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

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

493 **3.4. Impact assessment**

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

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

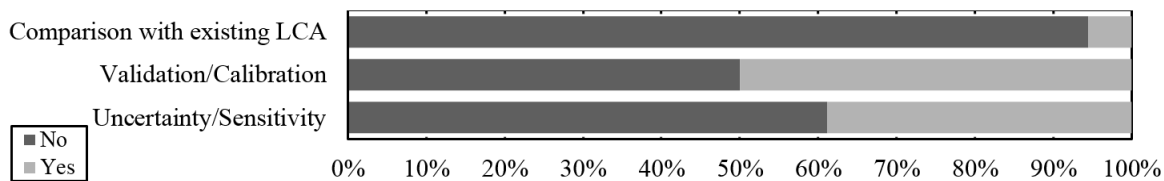
510

511 **3.5. Interpretation**

512 **LCA Uncertainty/Sensitivity Analysis.** No study refers to uncertainty analysis but more than 60% of the articles
513 conducted a sensitivity analysis (Figure 5). Sensitivity analysis can be performed to determine (a) which parameters
514 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*
 518 *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.



529
 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

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

567

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

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

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

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

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

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

577

578 **4. Discussions**

579 **4.1. Theoretical opportunity: How can the ABM enhance LCA?**

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

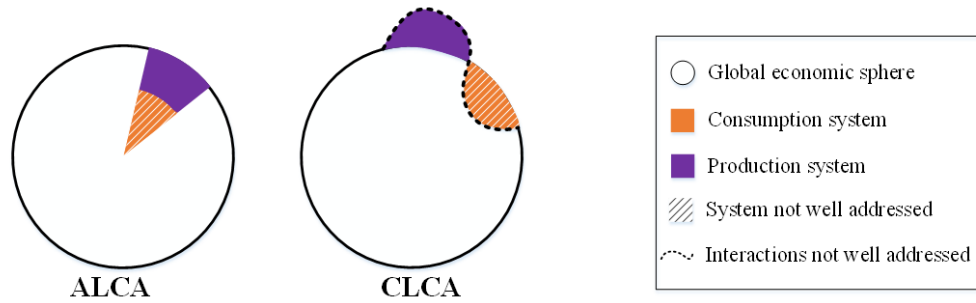
584 *Table 5 Potential contribution of ABM through the different LCA phases (MM stands for modelling methodology)*

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 dynamics	Environmental system	ALCA and CLCA
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.



607

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

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

649

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

661

662 **4.2. Recent LCA developments for which ABM could be relevant**

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

665 **Regionalization.** Regionalized LCA increase the results accuracy by considering site-specific conditions (Hellweg
666 and Milà i Canals, 2014). However, in practice, regionalization in LCA studies is rarely performed (Mutal and
667 Hellweg, 2009) because the acquisition of spatial data is challenging. To ease this step, GIS has been integrated in
668 the inventory and impact assessment modelling (Geyer *et al.*, 2010; Mutel, Pfister and Hellweg, 2012; Liu *et al.*,
669 2014) and the open source Brightway software (Brightway2, 2016) includes GIS capabilities in the LCA calculation.
670 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).

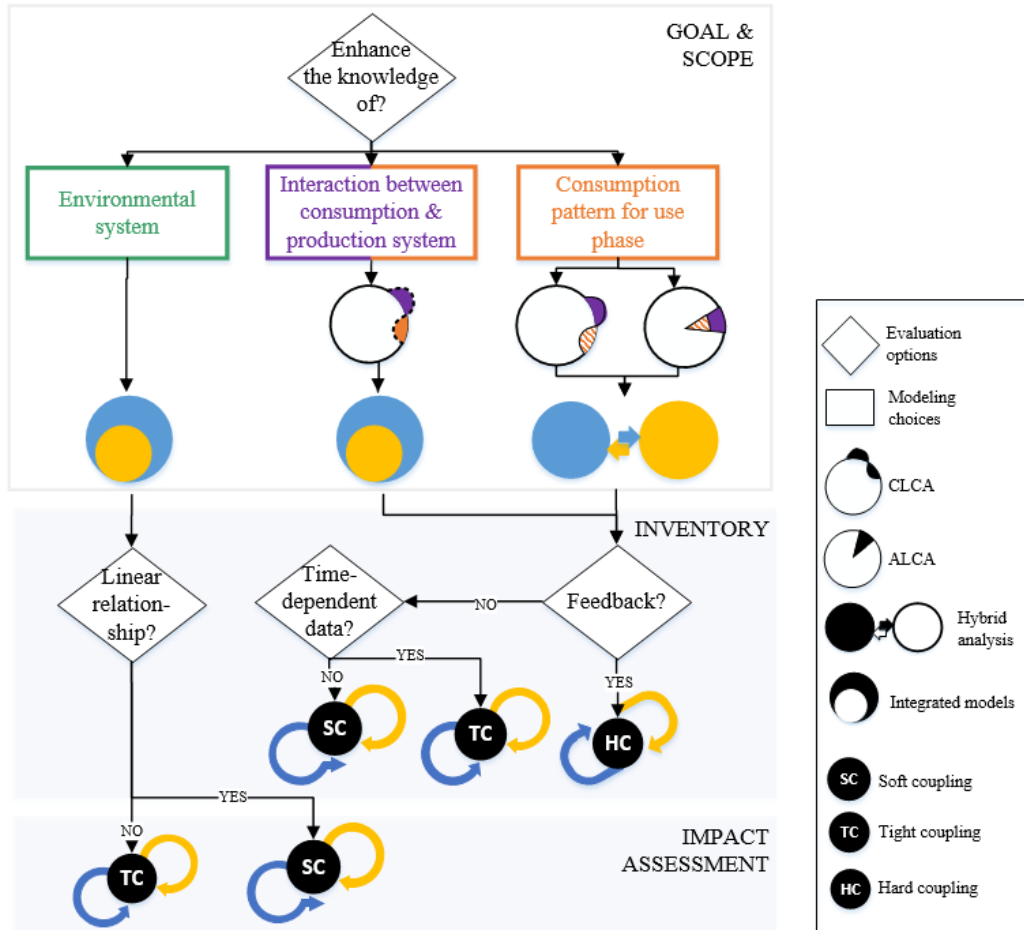
724 The degree of coupling profoundly influences the computational time, as well as the programming time. Hard-
725 coupling is meaningful when studies aim to integrate feedback on the environmental impact of the product in the
726 adaptive decision-making process or the self-learning mechanism of some 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

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



744
 745 *Figure 7 Guidance diagram for possible options of ABM and LCA coupling at different LCA phases, as proposed by ISO 14040 and 14044,*
 746 *concerning the type of coupling as defined Table 2 and the degree of coupling as defined Figure 1*

747 **4.4. Limitations and perspectives of the coupling methodology**

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

751 Coupling ABM with LCA requires expertise in both scientific domains. If integration of LCA in ABM is preferred,
 752 the LCA practitioner may know that the LCA computational structure defines agents as part of the life cycle
 753 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, Nikolíc 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.

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5. Conclusions

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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.

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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.

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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.

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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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6. References

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