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3 **Coupling economic models and environmental assessment methods to**
4 **support regional policies: a critical review**

5

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23

24

25 **Abstract**

26 This review analyses and compares the most promising methods to perform *ex ante* economic and
27 environmental assessment of policies at the *meso* scale, *i.e.* from local communities to subnational
28 regions. These methods called Economic-Environment Integrated Models (EEIM) are based on the
29 coupling of formalised economic modelling tools with environmental assessment methods. The
30 economic modelling tools considered are Input Output (IO) models, Computable General Equilibrium
31 (CGE) and Partial Equilibrium (PE) models, Agent-Based models (ABM), and System Dynamics (SD)
32 models, which we pair with environmental assessment methods such as Footprints (FP), Life Cycle
33 Assessment (LCA), or Material Flow Analysis (MFA). A grid of criteria is developed to perform a
34 qualitative rating of the EEIMs according to existing literature. The grid encompasses the detail level
35 of the economic modelling, the level of coupling between environmental and economic tools, the
36 quality and diversity of indicators, the ability to account for diverse indirect effects, spatial
37 differentiation, time aspects, and the coupled model usability. First, the results show that the couplings
38 do not perform on the same criteria, which shows complementarity to deal with diverse issues.
39 Second, overall, for most criteria, PE/CGE models coupled with FP/LCA ranked highest. Third, a few
40 case studies showed that couplings involving a third tool can be beneficial— for instance AB
41 modelling or MFA with PE/CGE-LCA/FP may allow to overcome some shortcomings such as agent
42 behaviour modelling or data availability for biophysical flows.

43

44 **Keywords**

45 Model coupling, Economic modelling, Environmental assessment, Integrated Assessment, Regional
46 policy, Sustainability

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56 **Abbreviations:** ABM, Agent Based Modelling; CGE, Computable General Equilibrium; EEIM,
57 Economic-Environment Integrated Model; FP, Footprint; IO, Input Output; LCA, Life Cycle
58 Assessment; LUC, Land Use Change; MFA, Material Flow Analysis; PE, Partial Equilibrium; SD,
59 System Dynamics.

60

61 **1 Introduction**

62 The transition towards sustainability requires efficient, effective, and feasible policies (European
63 Economic and Social Committee, 2016; European Parliament, 2014; OECD, 2013, 2011, 2007). These
64 policies need to be defined at different scales, and a particular emphasis is placed on subnational
65 policies, *i.e.* at the *meso* scale, which ranges from local communities to subnational regions.
66 Regulatory obligations regarding environmental assessment prior to public and private projects, plans,
67 and programmes have been implemented on this scale since the mid-1980s, particularly programmes

68 and projects involving territories and land planning under the responsibility of local authorities (EIA,
69 European Commission, 2016; SEA, European Parliament, 2001). Local and regional initiatives are
70 also promoted by International agreements (United Nations Conference on Environment and
71 Development, 1992) to support transitions towards sustainability, such as local Agenda 21 (Barrutia et
72 al., 2015), or by European authorities for green and circular economy strategies (European Economic
73 and Social Committee, 2016; Pitkänen et al., 2016).

74 These strategies are based on win-win assumptions, i.e. aiming at both environmental and economic
75 benefits (Loiseau et al., 2016). With respect to these objectives, quantitative tools are required to
76 provide an exhaustive assessment of both the environmental and economic impacts of subnational
77 projects.

78 In the economic field, environmental stakes have been integrated through valuation and cost-benefits
79 analysis methods (Costanza et al., 2014; Farber et al., 2002). Valuating environmental benefits into
80 monetary units can facilitate communication with a broad audience and raise societal awareness about
81 environmental issues. However, one major caveat of this method comes precisely from its strength, i.e.
82 by quantifying all impacts within the same unit, the specificities of the impacts are erased. Moreover,
83 monetary evaluation may have limits when it comes to assessing critical natural assets (Sunstein,
84 2005), e.g. the ozone layer or rare biodiversity (Pearce et al., 2006). To address these caveats, methods
85 coupling environmental tools with economic assessments are being developed, showing an ability to
86 provide indicators complementary to the monetary units.

87 In this paper, we specifically aim to identify and analyse the existing methods coupling economic
88 models and environment assessment tools to perform an integrated economic and environmental
89 assessment at the subnational scale. The paper focuses on tools that provide a quantitative evaluation
90 of economic effects and biophysical impacts specifically at this scale. On the one hand, different
91 economic modelling approaches have been identified to carry out studies at regional scales (Irwin et
92 al., 2010; Lemelin et al., 2008; Loveridge, 2004). Among these, input-output (IO) models are widely
93 used by regional economists. Regional declinations of models based on equilibrium theory have also
94 been established for many years (Irwin et al., 2010; Loveridge, 2004; Partridge and Rickman, 2010,
95 1998). Over the past 20 years, the use of tools developed primarily outside of the economic field, such
96 as agent-based modelling (ABM) (Chen et al., 2012; Fagiolo et al., 2007; Farmer and Foley, 2009;
97 Tesfatsion, 2017) or system dynamics (SD) (McCauley and Küffner, 2004; Radzicki, 2009; Sterman,
98 2005), has gained credibility and importance in modelling economic phenomena. On the other hand,
99 different environmental assessment tools can be used to quantify the impacts of territorial metabolism,
100 such as Life Cycle Assessment (LCA) (Loiseau et al., 2012), Material Flow Analysis (MFA)
101 (Courtonne et al., 2015; Hendriks et al., 2000; Huang et al., 2007; Kennedy et al., 2007), or
102 environmental Footprints (FP), e.g. Carbon Footprint (CF), Water Footprint (WF), or Ecological
103 Footprint (EF) (McGregor et al., 2008; K. Turner et al., 2012; Yu et al., 2010).

104 Some environmental-economic couplings have been reviewed for specific topics: climate change
105 mitigation (Pauliuk et al., 2017; Pehl et al., 2017), land use change (LUC), and indirect land use
106 change (ILUC) (Halog and Manik, 2011). However, no exhaustive analysis of all possible couplings
107 between the aforementioned economic and environmental assessment tools has so far been proposed.
108 This paper aims at contributing to filling this gap. More precisely, we have identified all types of
109 coupling of economic modelling and environmental assessment methods that exist in the scientific
110 literature and compared them in terms of their ability to provide exhaustive and quantitative
111 information to decision-makers at meso-scale.

112 This paper is structured as follows. Firstly, we briefly describe the main environmental tools and
113 economic models to highlight their main features. We then discuss how these models have been
114 coupled. Secondly, we perform bibliometric analysis to identify what types of coupling of economic
115 and environmental tools and methods that exist in the scientific literature have been conducted, and in

116 what number. Thirdly, we propose an analysis grid that includes the key criteria for a comprehensive
117 assessment at a meso scale. Then, we compare the coupled approaches through the proposed analysis
118 grid. Finally, we draw the main conclusions and perspectives to pave the way for future research on
119 coupling economic and environmental models at subnational scales.

120 **2 Overview of economic modelling approaches and environmental assessment** 121 **methods at the subnational scale**

122 This paper focuses on integrated assessments methods that have coupled existing and standardized
123 economic modelling tools with environment assessment methods. Before identifying these coupled
124 models in the literature, we provide a brief overview of each group of methods separately.

125 **2.1 Economic modelling approaches for the subnational scale**

126 The economic model review is based on the definition of *economics* as ‘the science dealing with the
127 allocation of scarce resources to meet unlimited needs’ (Samuelson and Nordhaus, 1992). We
128 therefore extend the review to all modelling tools that study human behaviour when it comes to
129 extracting, producing, transforming, exchanging and consuming resources, goods, and services, and
130 optimising these activities.

131 We consider five categories, depending on the way economic behaviours are represented (see figure 1
132 in SI-1). First, we distinguish empirical models from mixed theoretical-empirical models. Pure
133 empirical models refer to econometric models (EC) built on statistical analysis of economic data,
134 while theoretical-empirical models encompass all modelling tools built on a theoretical structure using
135 key variables calibrated with empirical data and/or statistical methods. We omitted from our analysis
136 purely theoretical models that provide qualitative insights as they only depict stylised behaviours.
137 Within mixed theoretical-empirical models, two consistent groups are considered.

138 The first group encompasses traditional economic models, which may exist in versions with
139 analytically solvable or numerically solvable structures. They are consistently used for subnational
140 applications, and are hence well described. This group includes input output (IO) models and
141 equilibrium theory models, i.e. Computable General Equilibrium (CGE) and Partial Equilibrium (PE)
142 models (Irwin et al., 2010; Lemelin et al., 2008; Lovelidge, 2004; Partridge and Rickman, 2010,
143 1998). The second group encompasses models sometimes referred to as *simulation* models. These
144 models have been developed in the computer era and have numerically solvable structures only. Their
145 use in economics applications has largely developed in the last 20 years (Borshchev and Filippov,
146 2004; Moon, 2017; Scholl, 2001). This second group includes Agent-Based modelling (ABM) (Chen
147 et al., 2012; Fagiolo et al., 2007; Farmer and Foley, 2009; Tesfatsion, 2017) and System Dynamics
148 (SD) (McCauley and Küffner, 2004; Radzicki, 2009; Sterman, 2005). Consequently, the review will
149 focus on five types of economic model, i.e. IO, CGE, PE, ABM, and SD. We provide their main
150 characteristics in table 1 and more information is given in the Supplementary Information (see SI-1).

<i>Economic models</i>	<i>IO and SAM</i>	<i>Econometric</i>	<i>General equilibrium</i>	<i>Partial Equilibrium</i>	<i>Agent-Based Modelling</i>	<i>System Dynamics</i>
<i>Characteristics</i>						
<i>Formalisation</i>	Linear relationship between economic output data embedded in tables	Relationship between various data from regressions	Supply and demand equilibrium based on econometrically estimated functions	Supply and demand equilibrium based on econometrically estimated functions	Behaviour rules	Stock, flows, and feedback loops
<i>Equations</i>	Linear	Linear and non-linear	Linear and non-linear	Linear and non-linear	Non-linear	Non-linear
<i>Time dynamic</i>	Static	Dynamic	Static and Dynamic	Static and Dynamic	Static and Dynamic	Dynamic
<i>Geographic scale</i>	From Meso to Macro	All scales	Rather macro oriented, meso scale exists	From Meso to Macro	Very Macro or very micro oriented	Very Macro or very micro oriented
<i>Strengths</i>	Tracks interindustry linkages Easy to implement	Accurate, time-pathed forecasts in the short term	Endogenous prices and substitution effects	Endogenous prices and substitution effects, simpler than general equilibrium	Freedom to model agent behaviour and interactions compared to analytical economic models	Freedom to implement any relevant variable and complex interactions
<i>Weaknesses</i>	Prices are fixed, no substitution effects. Tend to overestimate policy impacts	Predictive power tied to data quality and restricted to short term	Implementation cost, high data requirement, black box effect	Limited to one or a few economic sectors, less detailed socio-economic indicators than general equilibrium	Lacks standardisation/tractability, black box effect	Lacks standardisation/tractability, black box effect

152 **2.2 Environmental assessment methods**

153 Several tools can be used to assess the environmental impacts at the subnational scale. Loiseau et al.
154 (2012) provide a complete description and comparison of the main characteristics of all methods that
155 have been implemented at the territory scale. Among these, tools based on mono-footprint methods
156 such as the Ecological Footprint (EF) and tools based on metabolism studies such as Material Flow
157 Analysis (MFA) are notably widespread among practitioners. This is partly due to the existence of
158 guidelines and databases that make it possible to apply these tools to cities, subnational regions, and
159 nations. In addition, some of these methods provide indicators that are easily understandable by the
160 public. The authors show that Life Cycle assessment (LCA), although less used for territory analysis,
161 is a promising tool for assessing meso-scale objects. We provide an overview of the main
162 characteristics of these three types of environmental assessment method in the table below, i.e.
163 Footprint methods (Ecological, Carbon, and Water Footprint, FP), flow analysis (MFA or Substance
164 Flow Analysis, SFA), and LCA, and in the Supplementary Information (see SI- 2).
165

166 **2.3 Towards coupling of economic and environmental assessment tools**

167 Couplings between some of the aforementioned economic and environmental assessment tools have
168 been performed for 20 years in order to provide more exhaustive information to decision-makers.
169 Bouman et al. (2000) analysed the case of battery-related pollution using three different methods
170 simultaneously but separately, i.e. PE models, LCA, and MFA, and called for further integration of
171 these methods. Earles and Halog (2011), followed by Rajagopal (2017) and Roos and Ahlgren (2018),
172 reviewed methods using economic models to perform consequential LCA, which refers to an LCA
173 type where indirect effects induced by a change in the studied system are accounted for by expanding
174 its boundaries. Halog and Manik (2011) and Moon (2017) reviewed methods that used agent-based
175 modelling or system dynamics for sustainability assessments and proposed frameworks to compare
176 them. Integrated Assessment Models (IAMs), hybrid macroeconomic models developed in climate
177 change research to model industrial and consumption drivers of greenhouse gas (GHG) emissions in
178 various scenarios, were also coupled with LCA or MFA (Pauliuk et al., 2017; Pehl et al., 2017).
179 Model coupling ranges from the construction of *ad hoc* indicators (converting an economic output in
180 an environmental impact with a coefficient) to simultaneous use of different tools for the same case
181 study to more formalised coupling of models. We propose a simple classification of coupling between
182 low- and high-level couplings.
183 Low-level coupling encompasses couplings where economic and environment models are run
184 separately, using different variables. Output(s) from one model is (are) used as input(s) of the other
185 model, either at a single period (comparative) or through an iterative process (recursive). Numeric
186 interfaces can be used to automatize the recursive information transfer. High-level couplings describe
187 models that are linked and run together, involving variables from the economic and environmental
188 models in closed loops, e.g. a model where the behaviour of economic agents is environmentally
189 driven (preferences for environmental considerations in their utility function, production dependent on
190 environmental assets, etc.).
191 In both low and high-level couplings, the economic model often drives the entire coupled model. It
192 defines the level of aggregation of the model, the ability to model the interactions and indirect effects
193 in the assessed system – the foreground – or in its related systems – the background – and
194 subsequently, spatial consideration for impact assessment in the foreground. It also sets the time
195 dynamic. Thus, the economic model defines significantly the modelling abilities of the coupled model.

196 **3 Material and methods**

197 We present here the general approach we followed to select the literature to review and perform the
198 qualitative comparison of the couplings of the economic models and the environmental tools presented
199 in the precedent section. We base this comparison on a specific analysis grid including eight key
200 criteria.

201 **3.1 Bibliometric analysis**

202 The bibliometric analysis was focused on papers using couplings of economic and environmental
203 tools, hereafter called Economic-Environment Integrated Model (EEIM). We omitted approaches
204 using econometric forecast models for such couplings, as there were only two relevant papers. The
205 review eventually considers 15 types of EEIM.

206 We used the Scopus database¹ with a standardized process: in the query, the name - or names - of the
207 economic model type was crossed with one of the environmental assessment methods in the ‘abstract
208 – title – keywords’ category. The review was limited to articles published after 1990. This first
209 research provides insight into the use of EEIMs in the scientific literature. We provide the number of
210 papers found for each method and a keyword network analysis in the Supplementary Information (see
211 SI – 3).

212 We then selected articles within the results of this first search, based on the abstracts, retaining those
213 that showed a particular focus on the integration of economic modelling and environmental
214 assessment tools to model a region, economic sector(s) from the local to global scale, and sets of
215 economic agents. A few articles that were not obtained with the first search but that were often cited
216 were also added. We did not fully restrict the selection to regional applications at this point in order to
217 diversify the examples of EEIM. In this manner, we built a pool of case studies and articles for each of
218 the 15 EEIMs. We provide the full list in the Supplementary Information (see SI – 4).

219 **3.2 An analysis grid to evaluate integrated assessment methods**

220 We developed an analysis grid to carry out a transparent and argumentative comparison of the
221 EEIMs. We defined criteria that need to be considered when describing and analysing the couplings
222 following the approach proposed by Finnveden and Moberg (2005), Blanc et al. (2009) and Loiseau et
223 al. (2012). According to them, we made a distinction between criteria related to the main
224 characteristics of the EEIMs (i.e. descriptive criteria) and criteria related to the abilities of EEIMs.
225 These latter are used as qualitative criteria to rate the performances of the different types of couplings
226 to fit the purpose of performing an assessment of a meso scale entity, taking account of detailed
227 interdependencies between economic agents, environmental entities, at different spatial scales and
228 over time. This general approach allows characterising the different couplings and understanding their
229 appropriateness for different applications.

230 **3.2.1 Descriptive criteria**

231 The first group of criteria states the main characteristics of the EEIM:

- 232 (i) The first criterion deals with the objectives addressed by the coupling of models. In other
233 words, **what are the goals and scope of the study?** This qualitative criterion is proposed
234 to identify the object of the study, i.e. a complete geographic space such as a nation or a

¹ *Scopus is currently the best tool available for literature electronic search due to its wider subject and journal range compared to other databases.*

235 subnational region or single sector, and the main purpose of the study, e.g. a diagnosis or
236 policy eco-design, explorative scenario analysis, etc.

237

238 (ii) The second criterion analyses the intensity of the coupling between the economic and
239 environmental models, as explained in 2.1.3.

240

241 **3.2.2 Qualitative criteria**

242

243 The second group of criteria qualifies the main features of the EEIMs:

244 (iii) The third criterion addresses the **ability to model the studied system in a**
245 **comprehensive and detailed way**. It is decomposed into two dimensions. 1) The number
246 of economic sectors or products under consideration. The model represents either one or a
247 few related sectors or most to all economic sectors. 2) The level of aggregation or
248 disaggregation of the sectors or products. The type of economic model used mainly
249 determines the level of aggregation (using, for instance, the International Standard of
250 Industrial Classification of All Economic Activities (ISIC, 2007)). We distinguish:

251 a) Aggregated frameworks when categories correspond mostly to the ISIC top level,
252 usually with 10 to 20 or fewer sectors, each with a representative value.

253 b) Semi disaggregated frameworks, when it corresponds rather to the ISIC secondary level
254 from approximately 30 to approximately 60 sectors/products.

255 c) Very disaggregated frameworks, with more than 100 industries or products, more
256 detailed than the ISIC secondary level.

257 Further details are provided in the Supplementary Information (See SI-5a).

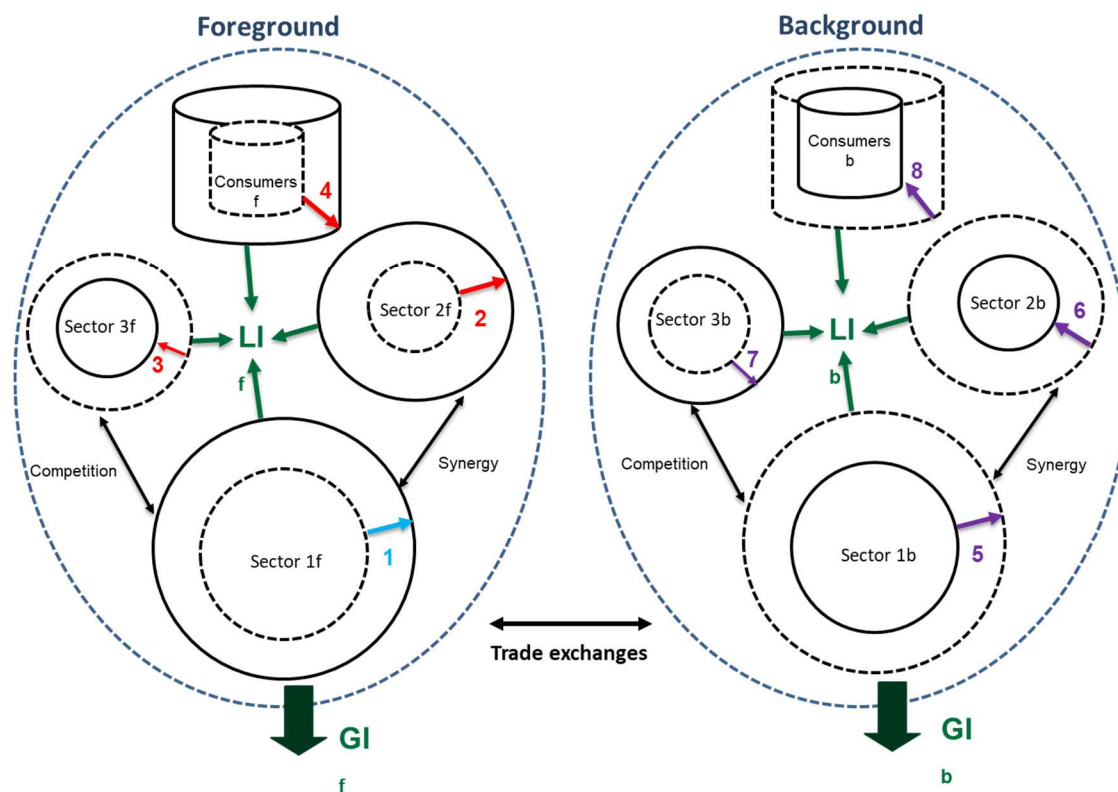
258

259 (iv) The fourth criterion evaluates **the ability of the EEIMs to provide a multicriteria**
260 **assessment**. This ability is essential to identify the distribution of socioeconomic or
261 environmental impacts (Finnveden et al., 2009), but also between environmental and
262 economic impacts. This final point is important to identify the win-win solutions for both
263 the environment and the economy (Porter and Linde, 1995). Usually, economic models
264 provide at least output indicators in monetary units (e.g. for a sector or country, such as
265 Gross Domestic Product) or quantities; other economic indicators may be given, such as
266 trade surplus, added value, consumer or producer surplus, tax revenue or policy budgetary
267 costs. At best, socioeconomic indicators such as jobs or wages are provided (Loveridge,
268 2004; Seung and Waters, 2006). Environmental indicators are related to pressures (i.e.
269 pollutant emissions or resource use), and certain methods (e.g. LCA) convert these
270 pressures into impacts on the environment, going further in the DPSIR (Drivers-Pressure-
271 State-Impact-Response) analytical framework proposed by the European Environment
272 Agency (EEA Report, Smeets and Weterings, 1999). The same rationale applies to
273 economic models. The more environmental flows (e.g. fossil and mineral resource use,
274 water, land use, greenhouse gas, pesticides, or particulates emissions, etc.) and economic
275 information (quantities, prices, and socioeconomic data) estimated the better.

276

277 (v) **The fifth criterion analyses the ability of the EEIMs to consider indirect effects**. If we
278 consider that the region or activity under study is the foreground system (see left side of
279 Figure 1), then, depending on the boundaries of the modelled system, two different types
280 of indirect effect are considered in relation to the foreground system. First, 'indirect
281 effects' can refer to the life cycle perspective and the system under study, which has

282 numerous sectoral and geographical linkages with the rest of the world due to increasing
 283 globalization. All these external linkages comprise the background systems (right side of
 284 Figure 1). A change in the foreground system can spread over the background system
 285 through trade exchanges. For instance, building a new biomass power plant in the
 286 foreground system may import part of its biomass from the background system, thus
 287 leading to crowding out of part of the biomass used by other industries or consumers in
 288 the background system. These indirect effects are represented in purple plain arrows on
 289 Figure 1 and refer to so-called ‘off-site impacts’. Other types of indirect effect are
 290 investigated in the literature and correspond to arrows 4 and 8 (see SI – 5b for more
 291 information). Second, indirect effects can also encompass all the modifications of product
 292 flows due to a change in the economic system after the implementation of a policy or the
 293 development of an infrastructure. For instance, building a biomass-fed power plant is
 294 likely to drive changes in (1) the biomass flows not only for the new plant but also for
 295 other industries (through competition or synergies) and (2) in the flows of final products
 296 (i.e. power and its substitutes) at the consumer level. These indirect effects at the
 297 foreground level are represented with red arrows in Figure 2 and refer to the so-called
 298 ‘consequential effects’.
 299



300
 301 **Figure 1- Representation of a set of indirect effects in the foreground and background**
 302 **systems**

303 In this example, sector *1f* benefits from a direct change, e.g. a policy, which increases its production
 304 capacity (arrow 1). Sector *2f* indirectly benefits from the policy *via* a synergetic relationship (arrow 2)
 305 while sector *3f* is badly affected through a competition relationship (arrow 3). Consumers *f* also indirectly
 306 benefit through price and revenue indirect effects (arrow 4). These three types of indirect effect (2, 3, 4)
 307 comprise the *consequential effects* of the policy. These changes induce changes in the local environmental
 308 impacts in the foreground LI_f and global impacts GI_f .

309 In the background system, all production sectors and consumers are affected through indirect *off-site*
310 effects (arrows 5, 6, 7, 8), which are transmitted through trade channels. These changes induce changes in
311 the local environmental impacts in the background Li_b and global impacts Gi_b .

312

313 (vi) The sixth criterion is based on the **ability of the EEIMs to consider spatial variability**.
314 The geographical representativeness of the activities or sectors under study increases the
315 robustness of the study and could be used to quantify regionalized impacts (Potting and
316 Hauschild, 2006). Explicit spatial modelling of economic activities in both the foreground
317 and background facilitates the consideration of spatial variability in impact assessment.

318

319 (vii) The seventh criterion discusses the **ability of the EEIMs to account for the temporal**
320 evolution of the system in the short, medium, and long term. In economics, short,
321 medium, and long terms are usually defined according to hypotheses on parameter
322 variability such as prices, capital formation, or elasticities, as well as technology
323 maturation or energy efficiency. We distinguish between static, dynamic non-recursive
324 and dynamic recursive frameworks. Dynamic recursive models allow for simulating of a
325 development path, while non-recursive models only simulate two time periods: initial and
326 modified.

327

328 (viii) The eighth and final criterion assesses the **ability of the EEIMs to be easily usable**. This
329 rating gathers appreciation of the availability of data as well as the amount of time and
330 technical knowledge required to run the EEIM and to implement the coupling, the level of
331 standardisation reached by each model, and/or the tools' abilities to provide results that
332 are understandable by stakeholders.

333

334 The EEIMs found in the literature are rated according to criteria (iii) to (viii), comparative to each
335 other, using a scale ranging from 1 to 4, with 4 being the most satisfying ability and 1 the least
336 satisfying. The rating system is detailed in Table 2.

Criteria	Description	Rating scale
Ability to model in a comprehensive and detailed way	Number of economic sectors or products: *One or a few related sectors *Most or all sectors are included. Level of aggregation of the economic sectors or products *Aggregated ('agricultural products') *Semi Aggregated ('cereals') *Disaggregated ('wheat')	1: one or a few sectors, aggregated products
		2: one or a few sectors, one or a few disaggregated products
		3: either disaggregated products for one or a few sectors or aggregated products for all sectors
		4: disaggregated products for all sectors
Ability to provide a multicriteria assessment	Each rating comprises a coupling of the economic models and the environmental models' ratings, scaled back from 1 to 4. Economic Indicators: Diversity and/or presence of socioeconomic indicators. Economic indicators are additive. Environmental indicators: diversity of environmental flows.	1 Information on quantities produced/consumed/transformed
		2 Exhaustive economic information (prices and quantities)
		3 Exhaustive economic information and socioeconomic impacts
		1 A few environmental flows
		2 Exhaustive environmental flows
		3 Exhaustive environmental impacts
Ability to model indirect effects: consequential and off-site effects	Consequential effects on the foreground/background *Intersectoral trade and intermediate consumptions effects *Market effects and product substitutions, rebound effects *Demand/supply thresholds, learning curves *Social behaviours (adoption...) Off-site effects from economic modelling and environmental tools' background modelling. Environmental background modelling and Economic background modelling	1: A few consequential effects with limited background interactions
		2: A few consequential effects with some background modelling / Many consequential effects with limited background modelling
		3: Many consequential effects with some background modelling
		4: Many consequential effects, with detailed background interactions
Ability to model Spatialisation	Case studies scale : Meso (Local/Subnational); Macro (National/International)	1: Rather macro level, global/unspatialised impacts
		2: Rather macro level, mostly global impacts, some foreground spatialisation
	Spatialisation of economic and environmental indicators in the foreground and/or background	3: Rather local/meso level, mostly global impacts, some foreground spatialisation
		4: Rather local/meso level, detailed spatialised foreground, some background spatialisation
Ability to account for temporal aspects	Time dynamics	1 Static
		2: Dynamic non-recursive
		3: Dynamic recursive
		4 : Dynamic recursive with dynamic environmental impacts
Usability	Data availability	1: Experimental couplings, specific data collection for the case studies
	Standardisation of models and coupling	2: Technical implementation, more or less data to collect
	Availability and technicality of models and coupling	3: Implementation accessible, consistent databases available
		4: Easy to implement, consistent databases available

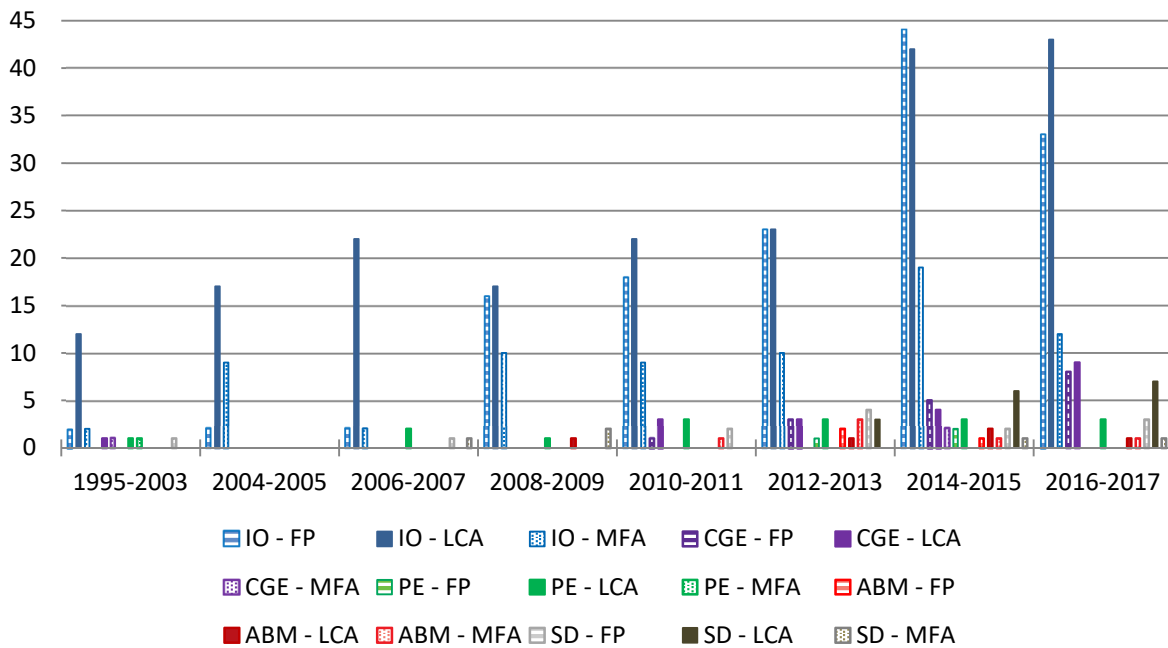
337 **Table 2 - Criteria description and rating system for qualitative comparison of models. IO=Input Output, ABM=agent-**
 338 **based modelling, SD=System Dynamic, PE=Partial Equilibrium, CGE=Computable General Equilibrium,**
 339 **FP=Footprint, MFA=Material Flow Analysis, LCA=Life Cycle Assessment**

340 **4 Results and discussion**

341 The results are presented as follows: first, we provide the results of the bibliometric analysis and then
 342 analyse the reviewed articles using the criteria grid developed in 3.2. Finally, we draw the main results
 343 and findings from the review.

344 **4.1 Quantitative results of the bibliometric analysis**

345 The evolution of the number of articles for each type of EEIM is plotted in Figure 2.



346

347 **Figure 2 - Number of articles per EEIM, for the period 1995-2004 and then every 2 years following. IO=Input Output,**
 348 **ABM=Agent-based modelling, SD=System Dynamic, PE=Partial Equilibrium, CGE=Computable General**
 349 **Equilibrium, FP=Footprint, MFA=Material Flow Analysis, LCA=Life Cycle Assessment**

350 Since the 1990s, couplings of economic IO models with various environmental assessment methods
 351 have been performed, with the first couplings conducted with LCA. Figure 2 shows that IO is by far
 352 the most used economic modelling type in EEIM. It is also the oldest form of economic and
 353 environmental model coupling. The use of CGE models, although limited, is clearly increasing at the
 354 end of the period, while the use of PE, ABM, and SD remains stable. This demonstrates a growing
 355 interest in more exhaustive approaches. Other types of EEIM are used on a much lower order of
 356 magnitude. Besides, EEIMs involving MFA appear to be less frequently used than those using LCA
 357 and FP.

358 **4.2 Comparison of the couplings through the proposed analysis grid**

359 We reviewed the pool of selected papers, i.e. 115 out of 536 papers found from the systematic search,
 360 using the analysis grid presented in section 2.3 in order to provide comparisons of the different
 361 EEIMs. We performed a qualitative scoring of the EEIMs based on the grid. The results are presented
 362 and discussed in the eight following sections. The complete ratings are summarised in the following
 363 Table 4 at the end of the section.

364

365 **4.2.1 Goal and scope of the study**

366 EEIMs based on IO couplings are best suited for diagnosis of geographic entities as a whole, as they
 367 generally encompass a large number of sectors at a reasonably disaggregated level (Minx et al., 2009).
 368 The best example is the coupling of footprints with Multi Regional Input Output (MRIO), i.e. IO
 369 tables gathering several figures at the regional or country scales, which allow the diagnosis to be
 370 extended from the foreground to related regions or countries (McGregor et al., 2008; Wiedmann,
 371 2009). In a complementary way, MFA couplings are most often used to perform a detailed diagnosis
 372 of a given sector or product family, e.g. metal flows and electronic components at a global or country
 373 scale (Bollinger et al., 2012; Bonnin et al., 2013; Choi et al., 2016; Dellink and Kandelaars, 2000;
 374 Elshkaki et al., 2004; Streicher-Porte et al., 2007).

375 EEIMs are also useful for national eco-design policy assessment, mostly with IO-FP (Allan et al.,
 376 2014; Chen et al., 2017) and CGE-FP, and in some cases IO-LCA and CGE-LCA. MFA couplings
 377 with ABM or SD are frequently used for recycling/circular economy eco-design. In the same vein,
 378 there are several examples of SD-based EEIMs addressing infrastructure or large-scale process
 379 efficiency (Bollinger et al., 2012; Feng et al., 2017; You et al., 2012). Finally, PE/CGE/ABM –
 380 Footprint/LCA EEIM are shown to be particularly used for scenario analysis related to agriculture,
 381 biofuels, and land use (Escobar et al., 2017; Marvuglia et al., 2017; Plevin et al., 2015; Rege et al.,
 382 2016). CGE and FP methods are oriented towards geographic entities rather than specific sectors, the
 383 opposite of PE and MFA. SD/ABM and LCA are rather process/sectoral oriented but are increasingly
 384 used at the subnational scale. The main properties and goals of the various EEIMs are given in Table
 385 3.

386

<i>Object of study</i> <i>Aim</i>	<i>Whole geographic entity</i>	<i>Product category/ Economic sector</i>
<i>Diagnosis</i>	IO-ALL, CGE-ALL, all-FP	All-MFA, (PE-all, all-LCA)
<i>Policy/Process</i> <i>Eco-design</i>	CGE – FP	SD-all, All-LCA, all-MFA
<i>Scenario</i> <i>analysis</i>	PE-ALL, CGE-ALL, IO-FP, all-LCA	PE/ABM-LCA; IO-MFA, SD-FP

387 **Table 3 – Preferred EEIM method sorted by questions and object of study**

388 *IO-ALL refers to any coupling of IO and an environmental assessment tool, i.e. IO-FP, IO-LCA, and*
 389 *IO-MFA. Similarly, all-FP refers to any coupling of an economic model and FP, i.e. IO-FP, CGE-FP,*
 390 *PE-FP, ABM-FP, and SD-FP.*

391 **4.2.2 Intensity of model coupling**

392 Most case studies present low-level couplings, i.e. the output of a model is used as inputs or
 393 parameters for the other. In most examples of IO/PE/CGE couplings, the economic model provides
 394 economic outputs with which an environmental impact assessment is performed. In fewer cases, the
 395 environmental modelling framework is used to provide data or parameter constraints for the economic
 396 modelling, for instance to model the effects of an environmental policy (Allan et al., 2014; Dellink and
 397 Kandelaars, 2000; Lenglet et al., 2017). It is noteworthy that in case studies where the coupling
 398 consists of a linear economic model whose outputs data feed a linear environmental assessment model,

399 higher coupling is useless. This remark applies to IO-FP and IO-LCA, depending on the LCI database
400 structure.

401 We identified two types of issue where high-level coupling is relevant. 1) When environmental
402 impacts have endogenous effects on the stock of capitals and/or the efficiency of the use of the
403 production factors; examples of high level coupling are SD-EF where the environmental consequences
404 of strategic decisions within an industry are embedded in the model (Feng et al., 2012; Jin et al.,
405 2009). 2) When economic agents internalise environmental policies in their decision process. Such a
406 feature is considered in Knoeri et al. (2013) and tested by Davis et al. (2009). It would allow us to
407 compare various environmental policy instruments, e.g. regulation, norm, communication, taxes, and
408 labelling.

409

410 ***4.2.3 Model comprehensiveness and detail***

411 Generally, IO models use multiregional tables containing more than 50 industries for all sectors of the
412 economy. CGE models, which are more aggregated, have fewer products, generally between 30 and
413 50. Most PE applications deal with 5 to 20 products for one or two related sectors such as agriculture
414 (Calzadilla et al., 2013; Morgan and Daigneault, 2015; Vázquez-Rowe et al., 2013), forestry (Earles et
415 al., 2013; Eriksson et al., 2012; Lenglet et al., 2017), or bioenergy (Bernard and Prieur, 2007; Escobar
416 et al., 2017; Rozakis et al., 2013). Although there are theoretically no restrictions to the number of
417 sectors represented, ABM models are found to be used for a single sector, with one or a few products;
418 for instance, switchgrass, dairy products, or wheat (Bichraoui et al., 2015; Marvuglia et al., 2017;
419 Morgan and Daigneault, 2015). In the same way, SD models are involved in EEIMs applied to a single
420 sector, with agriculture being well represented among SD-FP (El-Gafy, 2014; Feng et al., 2017; Inman
421 et al., 2016) with moderately disaggregated products. SD-LCA and SD-MFA are applied to industrial
422 sectors, and are very detailed in some case studies involving MFA coupling (Choi et al., 2016;
423 Elshkaki et al., 2004). Indeed, LCA was long restricted to product, process, or at best single economic
424 sectors (Pergola et al., 2013; Wood and Hertwich, 2013; You et al., 2012).

425 To sum up, IO-ALL models provide the most detailed and comprehensive representations of the
426 economy, followed by CGE-ALL and PE-ALL. ABM-ALL and SD-ALL papers comprise mixes of
427 case studies on specific products or sectors and a few studies of multisectoral systems.

428

429 ***4.2.4 Ability to provide a multicriteria assessment***

430 IO-ALL models provide the output in terms of quantities or value for the economic sector. Yet,
431 economic outputs may be translated into other socio-economic indicators using given exogenous
432 conversion coefficients.

433 PE and CGE are run with endogenous prices in addition to quantities, which allows us to calculate
434 producer and consumer surpluses. Nevertheless, most PE-ALL models focus on simpler economic
435 indicators, i.e. sector or product outputs in monetary units or quantities (Calzadilla et al., 2013;
436 Escobar et al., 2017; Vázquez-Rowe et al., 2013), with a few providing explicitly more detailed
437 economic assessments (Bernard and Prieur, 2007; Lenglet et al., 2017). Some CGE-ALL models are
438 able to deliver socioeconomic indicators as endogenous wages, employment, and tax amounts (Cong
439 et al., 2017; Cui et al., 2017; Dellink and Kandelaars, 2000). SD and ABM models usually process
440 socio-economic variables other than price and quantity (Tsfatsion, 2017) and thus tend to be able to
441 provide more socio-economic indicators derived from these variables. In this vein, Bravo et al. (2013)
442 give another level of information with an ABM model providing the household expenditures
443 associated with given consumption patterns. However, in the reviewed ABM-ALL and SD-ALL case
444 studies, the indicators are basic: cultivated areas in the many ABM-ALL models focus on the

445 agricultural sector or quantities for one or a few given sectors (Knoeri et al., 2013; Elshkaki et al.,
446 2004; Onat et al., 2016; Shrestha et al., 2012).

447 The possibilities offered by SD are more deeply exploited in some case studies to assess variables such
448 as capital investment and capital vintage (Davidsdottir and Ruth, 2005) or recycling rates (Streicher-
449 Porte et al., 2007).

450 As far as environmental performance is concerned, LCA was explicitly developed to perform
451 multicriteria environmental impact assessment and usually provides the highest number of impact
452 categories compared to other environmental assessment methods. All-MFA coupling provides one (or
453 more) indicator, mostly quantities for the materials whose flows are tracked, expressed in the same
454 unit (Kytzia et al., 2004; Matsubae-Yokoyama et al., 2009; Risku-Norja and Mäenpää, 2007).

455 For all-FP couplings, only one aggregated indicator is provided, ranging from emissions, as carbon
456 footprint inventories (Druckman and Jackson, 2009; McGregor et al., 2008; Minx et al., 2009), to
457 sectoral resource consumptions, as water footprint and land based ecological footprints tables (Feng et
458 al., 2012; Wang et al., 2013; Yu et al., 2010; Zhang and Anadon, 2014). In some cases, several
459 footprints are considered simultaneously to provide more than one footprint indicator. For instance,
460 some EF couplings connect the monetary outputs with a diversified set of impact categories on both
461 CO₂ emissions and resources consumption (Turner et al., 2007; Wiedmann et al., 2007) or carbon and
462 water footprint in order to diversify impacts measurements (Ewing et al., 2012; Galli et al., 2013;
463 Steen-Olsen et al., 2012).

464 To recap, the rating for this criteria being the combination of the economic model's rating and the
465 environmental tool's rating, CGE-LCA ranks best, followed by CGE-FP/MFA and PE/ABM/SD-
466 LCA. IO-FP/LCA and the couplings of PE, ABM, and SD with FP and MFA mix diverse economic
467 indicators with a few environmental flows. IO-MFA examples provide the least indicators.

468

469 ***4.2.5 Ability to consider diverse indirect effects: consequential and off-site effects***

470 We identified two aspects in terms of the ability to model indirect effects: first, the diversity of indirect
471 effects represented and, second, the possibility of assigning these indirect effects between the
472 foreground and the background. IO-ALL models track the linear relationships between the economic
473 sector, in terms of production or consumption. This comprises a simple type of consequential effect,
474 associated with exhaustive background modelling that allows detailed off-site impacts calculation.
475 These effects are as detailed as the IO model, ranging from MRIO models that represent the global
476 economy with more or less aggregated sectors and countries, to subnational scale interregional models
477 which provide a decomposed view of a national economy (Cazcarro et al., 2015; Cicas et al., 2007; Yi
478 et al., 2007).

479 PE/CGE-FP/LCA offer improved ability to deal with consequential effects. Providing endogenous
480 prices with production and consumption functions including price elasticities, equilibrium models
481 adjust more smoothly to changes in supply or demand. In particular, they offer more sophistication in
482 tracing factor market adjustments and resulting price and income induced effects (Turner et al., 2012).
483 PE/CGE-MFA offer similar economic interaction possibilities in the foreground and in the economic
484 background but fewer details on background flows, which limits off-site effect accounting.

485 ABM-FP/LCA models are used to test various behaviour effects such as new agricultural practices
486 adoption (Bakam et al., 2012; Bichraoui et al., 2015; Marvuglia et al., 2017; Morgan and Daigneault,
487 2015) or consumer behaviour (Bravo et al., 2013). Thus, these models, built on agent behaviour more
488 sophisticated than profit or utility maximisation as in the equilibrium model, provide consequential
489 effects that are particularly relevant at a local scale. In return, they usually lack endogenous prices.
490 This may be compensated for by coupling the ABM-ALL framework with an additional economic
491 mechanism for price information, such as a PE or CGE model (Morgan and Daigneault, 2015).

492 SD-FP/LCA are used to build ad-hoc models with detailed interactions chains for a sector or territories
493 at the local or meso scale (Inman et al., 2016; Shrestha et al., 2012). Compared to PE/CGE, they
494 emphasise material constraints over price and value mechanisms (Onat et al., 2016) and may lack
495 consequential effects between the foreground and a macro level background, due to the lack of
496 intersectoral details.

497 In the same way, ABM/SD-MFA makes it possible to model detailed systems with complex
498 consequential effects, with more features for intrasectoral interactions along the value chain, but may
499 lack intersectoral interactions.

500 To summarise, CGE-LCA provides the best combination of consequential and off-site effects.
501 CGE/FP-MFA, PE-LCA, and ABM/SD-LCA/MFA case studies combine several consequential effects
502 with some background modelling for off-site effects, and are thus rated 3 out of 4. EEIMs rated 2 out
503 of 4 are implemented either with many consequential effects and limited off-site effects – such as PE-
504 FP/MFA or ABM/SD-FP - or limited consequential effects and detailed off-site effects – such as IO-
505 FP/LCA. IO-MFA couplings have few indirect effects on both aspects.

506

507 *4.2.6 Spatial resolution*

508 We rate spatial resolution according to the resolution of the economic and environmental impacts, in
509 the foreground and background. Most EEIMs are applied at the national/global scale. Studies at the
510 meso/local scale account for approximately one-fifth of the sample set, with a few including detailed
511 spatial mapping or spatial differentiation.

512 Most IO-ALL models have a national level foreground resolution, with national and supranational
513 background resolution – « Rest of the world » regions in IO tables. IO-FP/LCA models reach meso
514 level resolution for foreground and background (G. Chen et al., 2017; Cicas et al., 2007; Yi et al.,
515 2007). At best, some IO-FP models such as Cazcarro et al. (2015) or Cong et al. (2017) couple local
516 level data with GIS data to build impact maps with a local level resolution for the foreground.

517 In the same way, many PE/CGE-FP/LCAs are built at a macro scale, and impacts are thus determined
518 for countries or macroregions (Calzadilla et al., 2013; Sanchez et al., 2012). PE/CGE-FP couplings -
519 particularly Water Footprint and Ecological Footprint - offer the most detailed regionalisation and
520 reach local and meso levels in terms of foreground and background resolution (Cazcarro et al., 2016;
521 Connor et al., 2015), as well as with SD-FP (Feng et al., 2017; Lu and Chen, 2017). Detailed spatial
522 resolution for background activities is useless when the environmental impacts investigated are global,
523 as is the case for studies that focus on GHG emissions (Earles et al., 2013; Escobar et al., 2017).
524 ABM-FP models are implemented with detailed spatial resolution (Morgan and Daigneault, 2015) as
525 well as basic data, e.g. unspatialised and restricted to a single sector of activity (Bakam et al., 2012).
526 ABM-LCA and SD-MFA are mostly conducted at a national scale. The least spatially accurate
527 couplings in our sample are CGE-MFA, SD-LCA, and ABM-MFA. Indeed, all-MFAs are often used
528 to assess a specific sector or product supply chain on a global scale, which may remove the need for
529 spatial representativeness.

530 To recap, the most spatially accurate case studies are conducted in all-FP couplings. PE-FP couplings
531 display the highest proportions of studies with subnational scale resolution of impacts. IO/CGE/ABM-
532 MFA as well as SD-LCA couplings have not been used below the national scale, with low background
533 resolution. Thus, these couplings have the lowest rating. IO/CGE/ABM-LCA and PE/SD-MFA have
534 been used for a few works with meso scale resolution of impacts and are thus rated just above.

535

536 *4.2.7 Time dynamic and temporal horizons*

537 A feature of IO-ALL models is the use of static accounting methods, e.g. IO-FP couplings (among
538 others (Ala-Mantila et al., 2014; W. Chen et al., 2017; Salvo et al., 2015). Dynamic non-recursive case
539 studies comprise either IO-ALL models as in Choi et al. (2010) and Risku-Norja and Mäenpää (2007)
540 or equilibrium models, e.g. CGE-MFA (Dellink and Kandelaars, 2000). That said, most of the
541 reviewed case studies comprise dynamic recursive models.

542 Regarding temporal horizons, technology changes are a key issue for both economic modelling and
543 environmental impact assessment. IO models are considered reliable only on short-term horizons;
544 nevertheless, IO-LCAs have been used to study the long-term effects of technology changes in the
545 energy sector (Finnveden et al., 2009; Gibon et al., 2015; Hertwich et al., 2015). PE and CGE models
546 can be adapted for various time horizons depending on hypotheses of capital formation, technology
547 changes, savings, or investments (Marvuglia et al., 2013; Partridge and Rickman, 2010). In our
548 sample, these range from medium/short term (Cazcarro et al., 2015; Escobar et al., 2017) to
549 medium/long term (Plevin et al., 2015, Eriksson et al., 2012) to very long term modelling (Calzadilla
550 et al., 2013; Earles et al., 2013). ABM-LCA has been used to take into account supply chain
551 evolutions (Davis et al., 2009) or emerging technology adoptions and impacts (Miller et al., 2013). SD
552 models may directly address the issue of parameter temporality, by implementing time dependant
553 variables in the model, allowing more reliable projections to be built. This is particularly performed in
554 SD-MFA coupling (Bollinger et al. (2012) Davidsdottir and Ruth (2005)) to include capital vintage
555 and investment in a system dynamics model of the wood industry.

556 To summarise, IO-FP/MFA couplings have the lowest abilities for time consistent modelling. IO-LCA
557 case studies comprise a mix of static and dynamic non-recursive. SD-MFA case studies have the best
558 features with which to deal with long-term effects in addition to having a recursive dynamic. All other
559 EEIMs are rated 3 out of 4, being used for various temporal horizons with a mostly dynamic recursive
560 time dynamic.

561

562 *4.2.8 Usability*

563 All the EEIMs require significant amounts of data but, for some, the databases are more available or
564 detailed. Data availability at the regional scale is a constant challenge compared to the national scale.
565 Developing regional datasets requires specific methods and is time-consuming (Irwin et al., 2010;
566 Ruault, 2014; Turner et al., 2007). At the national scale, IO-ALL models require less effort on that
567 specific point while others such as IO tables are widely available (Miller and Blair, 2009; Minx et al.,
568 2009; Wiedmann, 2009). Moreover, IO-FP/LCA may be synergic as IO tables provide a part of the
569 inventory. This advantage does not apply to IO-MFA, as connections between IO tables' values and
570 material flows data are not straightforward, with the exception of resource flows.

571 CGE models require much more time, econometric modelling skills, and important amounts of data,
572 particularly for regional studies (Allan et al., 2017). PE/CGE-FP/LCA as well as PE/CGE-MFA
573 couplings require additional efforts to fit the product categories of PE/CGE with FP/LCA inventories,
574 but linking models is not too difficult. Coupling with LCA is more time consuming when the Process-
575 LCA approach compared to the Economic Input Output-LCA approach (EIO-LCA)², although there
576 are available databases such as Ecoinvent (Wernet, G. et al., 2016).

² Process LCA is the original approach of itemising exhaustively inputs and outputs in a production process, with the limit of having to define the limits of the system's boundaries at some point. EIO-

577 ABMs require specific data on agent behaviour for consistent programming of the interaction rules
578 ((Borshchev and Filippov, 2004; Richiardi, 2003; Tesfatsion, 2017). If the ABM model's outputs are
579 simple – quantities, values –, coupling ABM with FP/LCA is straightforward, as it is in most ABM-
580 FP/LCA case studies. In Bravo et al. (2013) where consumption patterns are used or in Davis et al.
581 (2009) where the ABM model's outputs are integrated in the LCA database's technology matrix,
582 additional adaptations or design efforts are required. ABM usability is degraded in explorative
583 approaches as the latter consist in performing thousands of simulations when varying all agent
584 parameters, which may be computationally intensive and time consuming (Bollinger et al., 2012).
585 ABM-MFA studies are theoretical (Fernandez-Mena et al., 2016; Knoeri et al., 2013), and are thus
586 rated less usable than ABM-FP/LCA couplings.

587 SD economic models are far less widespread than other models among economists and are thus less
588 accessible (Radzicki, 2009). Specific design is required in all cases and the data requirements depend
589 on the project size. SD-FP and SD-MFA EEIMs are often built ad-hoc for a given micro system
590 (Inman et al. (2016) or El-Gafy (2014) for SD-FP or Choi et al. (2016) and Elshkaki et al. (2004) for
591 SD-MFA), or based on existing economic formalisations (Feng et al., 2017; Wei et al., 2013).

592 MFA does not benefit as much from existing databases and frameworks and always requires specific
593 work of data collection, a burden that can vary greatly depending on the scope of the studied system.
594 To sum up, IO-ALL models are the most accessible, followed by PE-ALL models, because of data
595 availability and manageable technicality. CGE-ALL, ABM-FP/LCA, and SD-FP are rated with an
596 average-low usability, due to various balances of important data collection needs on the one hand and
597 lesser spread and knowledge of the tools on the other hand. ABM-MFA and SD-LCA/MFA are
598 considered the most experimental couplings.

599

LCA relies on monetary inter-industry relationships described in EIO tables to catch indirect inputs and outputs.

600

	IO			CGE			PE			ABM			SD		
	IO - FP	IO - LCA	IO - MFA	CGE - FP	CGE - LCA	CGE - MFA	PE - FP	PE - LCA	PE - MFA	ABM - FP	ABM - LCA	ABM - MFA	SD - FP	SD - LCA	SD - MFA
Disaggregation	4	4	3	3	3	2	3	3	3	1	1	2	2	1	2
Multicriteria analysis	2	2	1	3	4	3	2	3	2	2	3	2	2	3	2
Off-site and consequential effects	2	2	1	3	4	3	2	3	2	2	3	3	2	3	3
Scale and spatialisation	3	2	1	3	2	1	4	3	2	3	2	1	3	1	2
Temporality	1	2	1	3	3	2	3	3	3	3	3	3	3	3	4
Usability	4	4	4	2	2	2	3	3	3	2	2	1	2	1	1

601

602

603

Table 4 - Tables for qualitative comparisons of EEIM based on selected criteria and qualitative rating. 1 (light grey) denotes the lowest ability to satisfy the criteria, 4 (dark grey) the highest

604 4.3 Main findings and perspectives

605 The results of the analysis of the EEIMs with regard to the six criteria are summarised in Table 4. It
606 should be noted that the couplings developed in the literature reviewed do not always fully represent
607 all the possibilities theoretically offered. For instance, most CGE-all models do not use all the
608 socioeconomic indicators that this type of economic model is able to generate. Table 4 shows that
609 some couplings score better than others. For instance, CGE-LCA has better overall scores than ABM-
610 FP. Nevertheless, the differences are not huge and adding together these qualitative grades to calculate
611 an overall grade and thus to rank each coupling would not be relevant. That said, some criteria such as
612 usability or disaggregation are more discriminant than others. Thus, a modeller with specific focus on
613 given criteria can choose a coupling more clearly over others. For instance, if usability is not
614 considered as an issue, CGE-FP/LCA appears as the most promising coupling.

615 All in all, PE/CGE-FP/LCA emerge as the most promising couplings according to their ratings. The
616 first difference among these couplings is the scale criterion for PE/CGE-LCA, for which there are
617 fewer examples of meso scale studies with detailed resolution than for PE/CGE-FP. CGE-FP/LCA
618 models provide more indicators than PE-FP/LCA. The higher level of disaggregation of PE-FP/LCA
619 models balances CGE-FP/LCA's comprehensive representation of economic sectors. Regarding other
620 couplings, IO-FP/LCA rank better in disaggregation and usability, and some SD-MFA couplings deal
621 better with temporality. ABM-ALL models allow us to integrate different indirect effects.

622 Some couplings show complementary features. In this vein, Morgan and Daigneault (2015) propose an
623 ABM-PE-FP model where the PE model provides endogenous prices and ABM farmer behaviour,
624 dealing with multiple consequential effects with a high spatial resolution. Hawkins et al. (2007) merge
625 IO, LCA, and MFA in order to obtain more detailed and diverse indicators. Bollinger et al. (2012)
626 propose coupling SD and ABM within an MFA, the first to model systemic macro effects and the
627 second to model economic agents' decisions. Coupling some of the methods, such as ABM and
628 PE/CGE – FP/LCA, appears as an interesting modelling perspective: such multiple couplings may
629 accrue advantages from several types of model and compensate some shortcomings. Other attempts to
630 couple several methods (multiple couplings) may be beneficial. SD-MFA methods that introduce non-
631 marginal, threshold, or long-term effects (Bollinger et al., 2012; Davidsdottir and Ruth, 2005) show
632 potential complementarity with PE/CGE models as they generate consequential effects that are usually
633 not dealt with by the equilibrium models. Other effects, which can be particularly relevant at the meso
634 scale, are heterogeneous social behaviours implemented with ABM (Bichraoui-Draper et al., 2015;
635 Bravo et al., 2013). Coupling any model with ABM may also help to address shortcomings on
636 subnational scale data availability, as in Bollinger et al. (2012) or Marvuglia et al. (2017), where
637 randomized behaviour parameters are used.

638 Building high couplings including feedback loops allowed us to include additional indirect long-term
639 effects, i.e. effects of environmental quality on economic productivity or internalisation of
640 environmental policies by economic agents – although this adds an additional layer of complexity.

641 The shortcoming to these multiple couplings and high-level coupling possibilities is that they induce a
642 risk of building heavy, ad-hoc, undecipherable models.

643 Among PE/CGE-FP/LCA couplings, the choice between PE and CGE depends on the need for
644 comprehensive socioeconomic indicators and the scope of the study. CGE-FP/LCA provide a more
645 exhaustive framework, when PE-FP/LCA are suitable for sector specific issues. PE/CGE-FP appear as
646 a better option than PE/CGE-LCA, as detailed local level spatial resolutions have been more
647 consistently implemented using this first type of coupling. Yet, LCA has a twofold advantage, i.e. it
648 complies with exhaustive environmental issues and it is possible to simplify an LCA into an FP while
649 the opposite is not possible. Overall, PE/CGE-LCA emerges as the most promising framework to

650 perform multicriteria assessment at the meso scale and we recommend testing associations of this
651 framework with other tools and models to improve its performance and add modelling abilities.
652

653 **5 Conclusion**

654 This paper aimed at clarifying the options for modelling and quantifying the environmental and
655 economic impacts of projects and development scenarios at the meso-scale, in order to support public
656 and private stakeholders' decision-making. We analysed through a systematic review the 15 possible
657 couplings out of 5 types of economic modelling method and 3 environmental assessment tools, i.e. IO,
658 PE, CGE, ABM, and SD models and FP, LCA, and MFA. For this purpose, we proposed a list of eight
659 criteria reflecting the ability of these couplings to meet these modelling objectives. The criteria
660 describe the ability to provide multi criteria assessment of a multisector socioeconomic system, in
661 interaction with other socioeconomic systems and the environment in its background, compliant with
662 life-cycle thinking, and including spatial variability and a time dynamic. For most of the 15 EEIMs
663 types, at least one or a few meso scale case studies existed. IO-FP/LCA/MFA couplings are the most
664 used and PE/CGE-FP/LCA couplings are also quite frequent while PE/CGE-MFA, SD-ALL, and
665 ABM-ALL are less represented. Data availability appears to be the major obstacle to developing
666 frameworks at subnational scales. More generally, EEIMs at all scales require multidisciplinary work
667 and technical skills to build model interfaces and one inherent risk of model coupling is to increase
668 complexity, leading to a black box effect and a loss of replicability.

669 Our findings are threefold. First, the proposed methodology showed that the EEIMs do not get the
670 same scores on the same criteria. They have different strengths and weaknesses, and may be best
671 suited to dealing with different policy questions. Considering the intensity of coupling criteria, almost
672 all paper reviewed used low-level coupling, indicating that it was sufficient for most studies. That said,
673 high-level couplings are needed: to explore long-term development path, where feedback loops
674 between the environment and the economic system can have significant effect. It is especially true for
675 models consistent with strong sustainability objectives, for which hard constraints on environmental
676 states are more likely to induce major retroactions on the repartition of economic activities than
677 substitutions defined in a weak sustainability framework by environment value and efficiency of
678 production factors. Second, we identified that PE/CGE models coupled with FP/LCA ranked best
679 considering most criteria. These findings urge to develop further regionalised versions of PE/CGE
680 models and an LCA database, paying a particular attention to the validation of these macro-oriented
681 methods when transposed at the *meso* scale.

682 Nevertheless, none of the couplings fully answered to all the aforementioned expectations for an
683 exhaustive meso-scale assessment model. Other couplings have strengths such as innovative ways to
684 deal with complex non-marginal changes and indirect effects, such as ABM-LCA/MFA or SD-MFA.

685 Third, a few case studies showed that couplings involving a third tool can be beneficial— for instance
686 AB modelling or MFA with PE/CGE-LCA/FP allow to overcome some shortcomings – respectively
687 regarding agent behaviour modelling or data availability on biophysical flows. This finding suggests
688 testing the associations of PE/CGE-LCA/FP couplings with other tools and models to improve its
689 performance and add modelling abilities, and eventually, developing a regional EEIM able to address
690 all criteria with the best rating.

691 Our methodology shows some limits. First, the set of criteria analysed is limited and we restricted our
692 analysis to those that we considered as important regarding the design of meso scales policies. Second,
693 the rating is based on the existing literature, which is recent, and do not always reflect the full abilities
694 of the couplings used. Some couplings could improve in the future, making the ratings and the mutual
695 rankings dynamic.

696 Third, the case studies reviewed do not always apply to the same questions, limiting the comparison of
697 their results. One way to overcome this issue would be to use the different methods to answer a same
698 question, as done in Bouman et al. (2000).

699 Eventually, our review was focused on models and tools that can be used to quantify impacts on
700 environmental and economic dimensions. The resulting indicators can be used to go further in the
701 assessment by using optimisation tools such as Data Envelopment Analysis (DEA) or decision-making
702 approaches such as Multi Criteria Analysis (MCA). These complementary approaches will strengthen
703 the benefits of EEIMs in a decision-making context. Ultimately, all these tools and methods add food
704 for thought to develop the economic and environmental dimensions of the Life Cycle Sustainability
705 Assessment (LCSA) framework (Guinée and Heijungs, 2011). This paves the way for future research.
706

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712 **7 References**

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