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

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Abstract

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

Keywords

Model coupling, Economic modelling, Environmental assessement, Integrated Assessment, Regional policy, Sustainability

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

1 Introduction

The transition towards sustainability requires efficient, effective, and feasible policies (European Economic and Social Committee, 2016; European Parliament, 2014; OECD, 2013, 2011, 2007). These policies need to be defined at different scales, and a particular emphasis is placed on subnational policies, i.e. at the *meso* scale, which ranges from local communities to subnational regions. Regulatory obligations regarding environmental assessment prior to public and private projects, plans, and programmes have been implemented on this scale since the mid-1980s, particularly programmes and projects involving territories and land planning under the responsibility of local authorities (EIA, European Commission, 2016; SEA, European Parliament, 2001). Local and regional initiatives are also promoted by International agreements (United Nations Conference on Environment and Development, 1992) to support transitions towards sustainability, such as local Agenda 21 (Barrutia et al., 2015), or by European authorities for green and circular economy strategies (European Economic and Social Committee, 2016; Pitkänen et al., 2016).

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

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

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

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

This paper is structured as follows. Firstly, we briefly describe the main environmental tools and economic models to highlight their main features. We then discuss how these models have been coupled. Secondly, we perform bibliometric analysis to identify what types of coupling of economic and environmental tools and methods that exist in the scientific literature have been conducted, and in what number. Thirdly, we propose an analysis grid that includes the key criteria for a comprehensive assessment at a meso scale. Then, we compare the coupled approaches through the proposed analysis grid. Finally, we draw the main conclusions and perspectives to pave the way for future research on coupling economic and environmental models at subnational scales.

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

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

2.1 Economic modelling approaches for the subnational scale

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

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

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

Economic models / Characteristics	IO and SAM	Econometric	General equilibrium	Partial Equilibrium	Agent-Based Modelling	System Dynamics
Formalisation	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
Equations	Linear	Linear and non-linear	Linear and non-linear	Linear and non-linear	Non-linear	Non-linear
Time dynamic	Static	Dynamic	Static and Dynamic	Static and Dynamic	Static and Dynamic	Dynamic
Geographic scale	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
Strengths	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
Weaknesses	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

Table 1 - Main characteristics of regional economic modelling tools

2.2 Environmental assessment methods

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

2.3 Towards coupling of economic and environmental assessment tools

Couplings between some of the aforementioned economic and environmental assessment tools have been performed for 20 years in order to provide more exhaustive information to decision-makers. Bouman et al. (2000) analysed the case of battery-related pollution using three different methods simultaneously but separately, i.e. PE models, LCA, and MFA, and called for further integration of these methods. Earles and Halog (2011), followed by Rajagopal (2017) and Roos and Ahlgren (2018), reviewed methods using economic models to perform consequential LCA, which refers to an LCA type where indirect effects induced by a change in the studied system are accounted for by expanding its boundaries. Halog and Manik (2011) and Moon (2017) reviewed methods that used agent-based modelling or system dynamics for sustainability assessments and proposed frameworks to compare them. Integrated Assessment Models (IAMs), hybrid macroeconomic models developed in climate change research to model industrial and consumption drivers of greenhouse gas (GHG) emissions in various scenarios, were also coupled with LCA or MFA (Pauliuk et al., 2017; Pehl et al., 2017).

Model coupling ranges from the construction of *ad hoc* indicators (converting an economic output in an environmental impact with a coefficient) to simultaneous use of different tools for the same case study to more formalised coupling of models. We propose a simple classification of coupling between low- and high-level couplings.

Low-level coupling encompasses couplings where economic and environment models are run separately, using different variables. Output(s) from one model is (are) used as input(s) of the other model, either at a single period (comparative) or through an iterative process (recursive). Numeric interfaces can be used to automatize the recursive information transfer. High-level couplings describe models that are linked and run together, involving variables from the economic and environmental models in closed loops, e.g. a model where the behaviour of economic agents is environmentally driven (preferences for environmental considerations in their utility function, production dependent on environmental assets, etc.).

In both low and high-level couplings, the economic model often drives the entire coupled model. It defines the level of aggregation of the model, the ability to model the interactions and indirect effects in the assessed system – the foreground – or in its related systems – the background – and subsequently, spatial consideration for impact assessment in the foreground. It also sets the time dynamic. Thus, the economic model defines significantly the modelling abities of the coupled model.

3 Material and methods

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

3.1 Bibliometric analysis

The bibliometric analysis was focused on papers using couplings of economic and environmental tools, hereafter called Economic-Environment Integrated Model (EEIM). We omitted approaches using econometric forecast models for such couplings, as there were only two relevant papers. The review eventually considers 15 types of EEIM.
We used the Scopus database[1] with a standardized process: in the query, the name - or names - of the economic model type was crossed with one of the environmental assessment methods in the 'abstract – title – keywords' category. The review was limited to articles published after 1990. This first research provides insight into the use of EEIMs in the scientific literature. We provide the number of papers found for each method and a keyword network analysis in the Supplementary Information (see SI – 3).
We then selected articles within the results of this first search, based on the abstracts, retaining those that showed a particular focus on the integration of economic modelling and environmental assessment tools to model a region, economic sector(s) from the local to global scale, and sets of economic agents. A few articles that were not obtained with the first search but that were often cited were also added. We did not fully restrict the selection to regional applications at this point in order to diversify the examples of EEIM. In this manner, we built a pool of case studies and articles for each of the 15 EEIMs. We provide the full list in the Supplementary Information (see SI – 4).

3.2 An analysis grid to evaluate integrated assessment methods

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

3.2.1 Descriptive criteria

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

(i) The first criterion deals with the objectives addressed by the coupling of models. In other words, **what are the goals and scope of the study**? This qualitative criterion is proposed to identify the object of the study, i.e. a complete geographic space such as a nation or a subnational region or single sector, and the main purpose of the study, e.g. a diagnosis or policy eco-design, explorative scenario analysis, etc.

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

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

3.2.2 Qualitative criteria

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

(iii) The third criterion addresses the **ability to model the studied system in a comprehensive and detailed way**. It is decomposed into two dimensions. 1) The number of economic sectors or products under consideration. The model represents either one or a few related sectors or most to all economic sectors. 2) The level of aggregation or disaggregation of the sectors or products. The type of economic model used mainly determines the level of aggregation (using, for instance, the International Standard of Industrial Classification of All Economic Activities (ISIC, 2007)). We distinguish:
a) Aggregated frameworks when categories correspond mostly to the ISIC top level, usually with 10 to 20 or fewer sectors, each with a representative value.
b) Semi disaggregated frameworks, when it corresponds rather to the ISIC secondary level from approximately 30 to approximately 60 sectors/products.
c) Very disaggregated frameworks, with more than 100 industries or products, more detailed than the ISIC secondary level.
Further details are provided in the Supplementary Information (See SI-5a).

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

(v) **The fifth criterion analyses the ability of the EEIMs to consider indirect effects.** If we consider that the region or activity under study is the foreground system (see left side of Figure 1), then, depending on the boundaries of the modelled system, two different types of indirect effect are considered in relation to the foreground system. First, ‘indirect effects’ can refer to the life cycle perspective and the system under study, which has numerous sectoral and geographical linkages with the rest of the world due to increasing globalization. All these external linkages comprise the background systems (right side of Figure 1). A change in the foreground system can spread over the background system through trade exchanges. For instance, building a new biomass power plant in the foreground system may import part of its biomass from the background system, thus leading to crowding out of part of the biomass used by other industries or consumers in the background system. These indirect effects are represented in purple plain arrows on Figure 1 and refer to so-called 'off-site impacts'. Other types of indirect effect are investigated in the literature and correspond to arrows 4 and 8 (see SI – 5b for more information). Second, indirect effects can also encompass all the modifications of product flows due to a change in the economic system after the implementation of a policy or the development of an infrastructure. For instance, building a biomass-fed power plant is likely to drive changes in (1) the biomass flows not only for the new plant but also for other industries (through competition or synergies) and (2) in the flows of final products (i.e. power and its substitutes) at the consumer level. These indirect effects at the foreground level are represented with red arrows in Figure 2 and refer to the so-called 'consequential effects'.

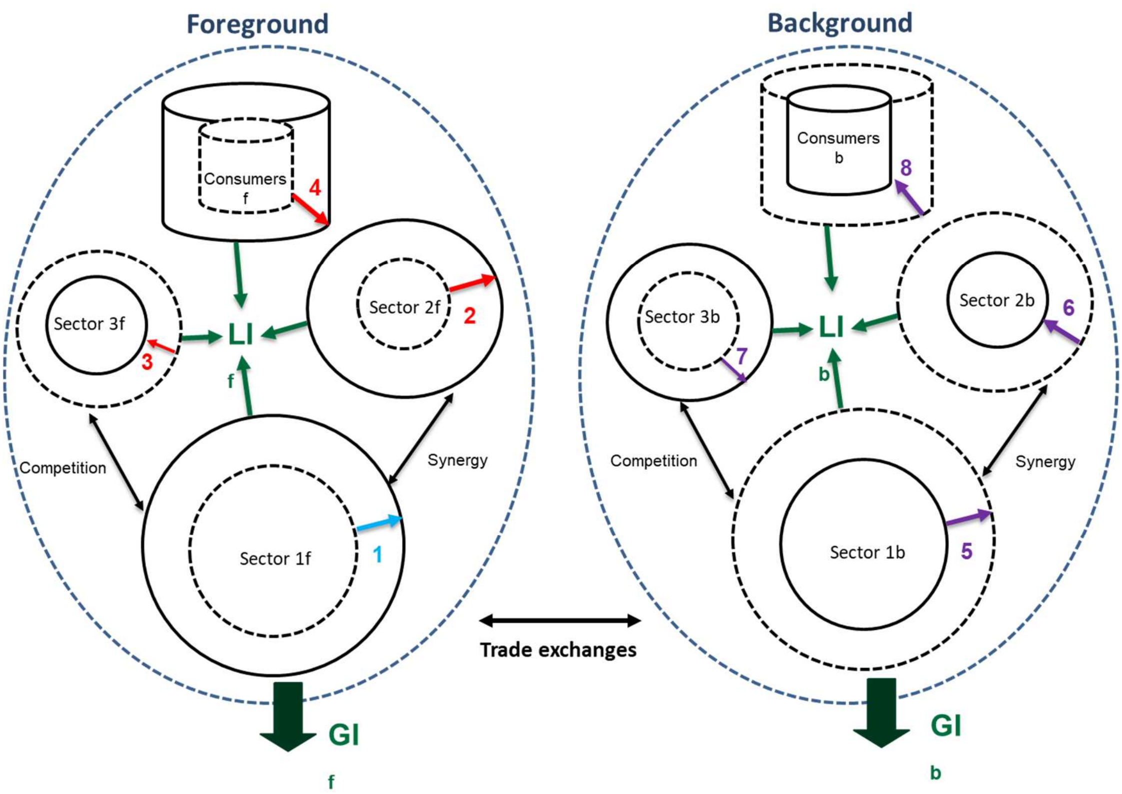

Figure 1- Representation of a set of indirect effects in the foreground and background systems

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

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

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

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

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

The EEIMs found in the literature are rated according to criteria (iii) to (viii), comparative to each other, using a scale ranging from 1 to 4, with 4 being the most satisfying ability and 1 the least 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.	1 Information on quantities produced/consumed/transformed
		2 Exhaustive economic information (prices and quantities)
		3 Exhaustive economic information and socioeconomic impacts
	Environmental indicators: diversity of environmental flows.	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
		3: Rather local/meso level, mostly global impacts, some foreground spatialisation
	Spatialisation of economic and environmental indicators in the foreground and/or background	4: Rather local/meso level, detailed spatialised foreground, some background spatialisation
Ability to accountfor temporal aspects	Time dynamics	1 Static
		2: Dynamic non-recursive
		3: Dynamic recursive
		4 : Dynamic recursive with dynamic environmental impacts
Usability	Data availability Standardisation of models and coupling Availability and technicality of models and coupling	1: Experimental couplings, specific data collection for the case studies
		2: Technical implementation, more or less data to collect
		3: Implementation accessible, consistent databases available
		4: Easy to implement, consistent databases available

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

4 Results and discussion

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

4.1 Quantitative results of the bibliometric analysis

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

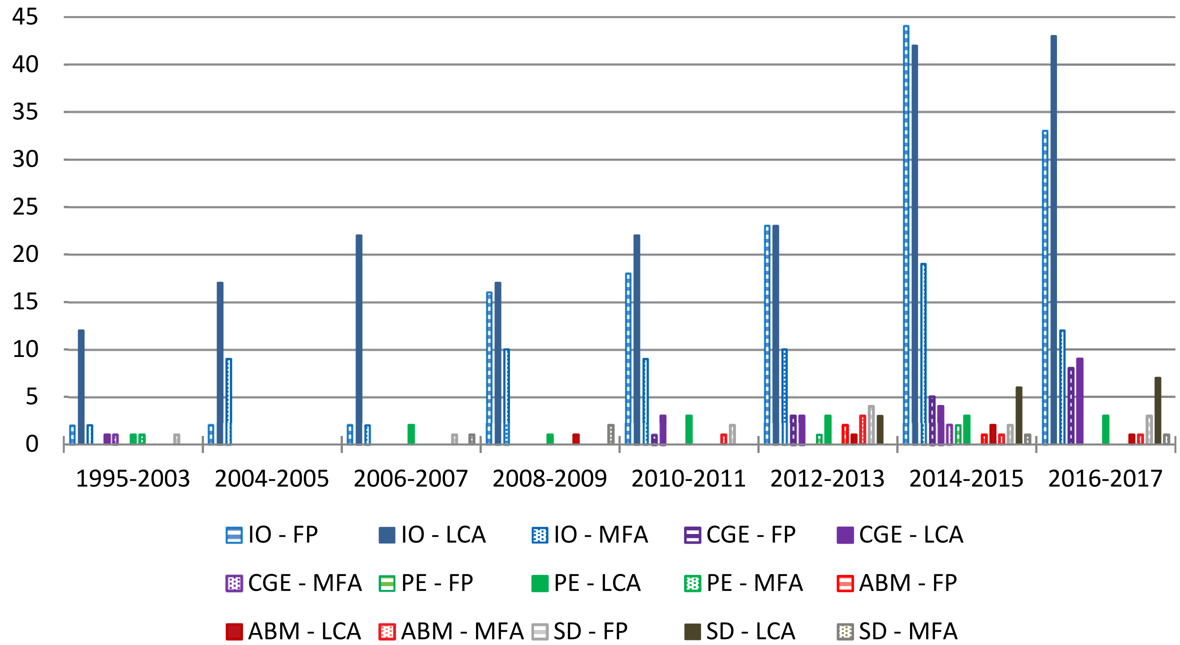

Figure 2 - Number of articles per EEIM, for the period 1995-2004 and then every 2 years following. IO=Input Output, ABM=Agent-based modelling, SD=System Dynamic, PE=Partial Equilibrium, CGE=Computable General Equilibrium, FP=Footprint, MFA=Material Flow Analysis, LCA=Life Cycle Assessment

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

4.2 Comparison of the couplings through the proposed analysis grid

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

4.2.1 Goal and scope of the study

EEIMs based on IO couplings are best suited for diagnosis of geographic entities as a whole, as they generally encompass a large number of sectors at a reasonably disaggregated level (Minx et al., 2009). The best example is the coupling of footprints with Multi Regional Input Output (MRIO), i.e. IO tables gathering several figures at the regional or country scales, which allow the diagnosis to be extended from the foreground to related regions or countries (McGregor et al., 2008; Wiedmann, 2009). In a complementary way, MFA couplings are most often used to perform a detailed diagnosis of a given sector or product family, e.g. metal flows and electronic components at a global or country scale (Bollinger et al., 2012; Bonnin et al., 2013; Choi et al., 2016; Dellink and Kandelaars, 2000; Elshkaki et al., 2004; Streicher-Porte et al., 2007).
EEIMs are also useful for national eco-design policy assessment, mostly with IO-FP (Allan et al., 2014; Chen et al., 2017) and CGE-FP, and in some cases IO-LCA and CGE-LCA. MFA couplings with ABM or SD are frequently used for recycling/circular economy eco-design. In the same vein, there are several examples of SD-based EEIMs addressing infrastructure or large-scale process efficiency (Bollinger et al., 2012; Feng et al., 2017; You et al., 2012). Finally, PE/CGE/ABM – Footprint/LCA EEIM are shown to be particularly used for scenario analysis related to agriculture, biofuels, and land use (Escobar et al., 2017; Marvuglia et al., 2017; Plevin et al., 2015; Rege et al., 2016). CGE and FP methods are oriented towards geographic entities rather than specific sectors, the opposite of PE and MFA. SD/ABM and LCA are rather process/sectoral oriented but are increasingly used at the subnational scale. The main properties and goals of the various EEIMs are given in Table 3.

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

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

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

4.2.2 Intensity of model coupling

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

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

4.2.3 Model comprehensiveness and detail

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

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

4.2.4 Ability to provide a multicriteria assessment

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

PE and CGE are run with endogenous prices in addition to quantities, which allows us to calculate producer and consumer surpluses. Nevertheless, most PE-ALL models focus on simpler economic indicators, i.e. sector or product outputs in monetary units or quantities (Calzadilla et al., 2013; Escobar et al., 2017; Vázquez-Rowe et al., 2013), with a few providing explicitly more detailed economic assessments (Bernard and Prieur, 2007; Lenglet et al., 2017). Some CGE-ALL models are able to deliver socioeconomic indicators as endogenous wages, employment, and tax amounts (Cong et al., 2017; Cui et al., 2017; Dellink and Kandelaars, 2000). SD and ABM models usually process socio-economic variables other than price and quantity (Tesfatsion, 2017) and thus tend to be able to provide more socio-economic indicators derived from these variables. In this vein, Bravo et al. (2013) give another level of information with an ABM model providing the household expenditures associated with given consumption patterns. However, in the reviewed ABM-ALL and SD-ALL case studies, the indicators are basic: cultivated areas in the many ABM-ALL models focus on the agricultural sector or quantities for one or a few given sectors (Knoeri et al., 2013; Elshkaki et al., 2004; Onat et al., 2016; Shrestha et al., 2012).

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

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

For all-FP couplings, only one aggregated indicator is provided, ranging from emissions, as carbon footprint inventories (Druckman and Jackson, 2009; McGregor et al., 2008; Minx et al., 2009), to sectoral resource consumptions, as water footprint and land based ecological footprints tables (Feng et al., 2012; Wang et al., 2013; Yu et al., 2010; Zhang and Anadon, 2014). In some cases, several footprints are considered simultaneously to provide more than one footprint indicator. For instance, some EF couplings connect the monetary outputs with a diversified set of impact categories on both CO_2 emissions and resources consumption (Turner et al., 2007; Wiedmann et al., 2007) or carbon and water footprint in order to diversify impacts measurements (Ewing et al., 2012; Galli et al., 2013; Steen-Olsen et al., 2012).

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

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

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

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

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

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

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

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

4.2.6 Spatial resolution

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

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

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

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

4.2.7 Time dynamic and temporal horizons

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

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

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

4.2.8 Usability

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

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

ABMs require specific data on agent behaviour for consistent programming of the interaction rules (Borshchev and Filippov, 2004; Richiardi, 2004; Tesfatsion, 2017). If the ABM model's outputs are simple – quantities, values –, coupling ABM with FP/LCA is straightforward, as it is in most ABM-FP/LCA case studies. In Bravo et al. (2013) where consumption patterns are used or in Davis et al. (2009) where the ABM model's outputs are integrated in the LCA database's technology matrix,

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

additional adaptations or design efforts are required. ABM usability is degraded in explorative approaches as the latter consist in performing thousands of simulations when varying all agent parameters, which may be computationally intensive and time consuming (Bollinger et al., 2012). ABM-MFA studies are theoretical (Fernandez-Mena et al., 2016; Knoeri et al., 2013), and are thus rated less usable than ABM-FP/LCA couplings.

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

MFA does not benefit as much from existing databases and frameworks and always requires specific work of data collection, a burden that can vary greatly depending on the scope of the studied system.

To sum up, IO-ALL models are the most accessible, followed by PE-ALL models, because of data availability and manageable technicality. CGE-ALL, ABM-FP/LCA, and SD-FP are rated with an average-low usability, due to various balances of important data collection needs on the one hand and lesser spread and knowledge of the tools on the other hand. ABM-MFA and SD-LCA/MFA are considered the most experimental couplings.

	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

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

4.3 Main findings and perspectives

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

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

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

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

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

Among PE/CGE-FP/LCA couplings, the choice between PE and CGE depends on the need for comprehensive socioeconomic indicators and the scope of the study. CGE-FP/LCA provide a more exhaustive framework, when PE-FP/LCA are suitable for sector specific issues. PE/CGE-FP appear as a better option than PE/CGE-LCA, as detailed local level spatial resolutions have been more consistently implemented using this first type of coupling. Yet, LCA has a twofold advantage, i.e. it complies with exhaustive environmental issues and it is possible to simplify an LCA into an FP while the opposite is not possible. Overall, PE/CGE-LCA emerges as the most promising framework to perform multicriteria assessment at the meso scale and we recommend testing associations of this framework with other tools and models to improve its performance and add modelling abilities.

5 Conclusion

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

Our findings are threefold. First, the proposed methodology showed that the EEIMs do not get the same scores on the same criteria. They have different strengths and weaknesses, and may be best suited to dealing with different policy questions. Considering the intensity of coupling criteria, almost all paper reviewed used low-level coupling, indicating that it was sufficient for most studies. That said, high-level couplings are needed: to explore long-term development path, where feeback loops between the environment and the economic system can have significant effect. It is especially true for models consistent with strong sustainability objectives, for which hard constraints on environmental states are more likely to induce major retroactions on the repartition of economic activities than substitutions defined in a weak sustainability framework by environment value and efficiency of production factors.

Second, we identified that PE/CGE models coupled with FP/LCA ranked best considering most criteria. These findings urge to develop further regionalised versions of PE/CGE models and an LCA database, paying a particular attention to the validation of these macro-oriented methods when transposed at the *meso* scale.

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

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

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

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

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

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