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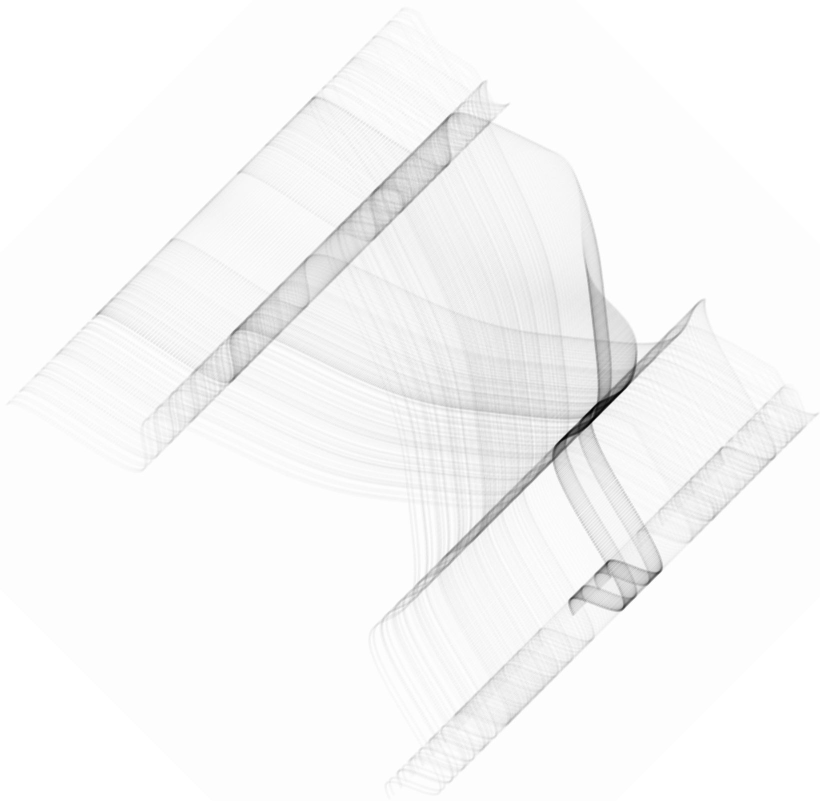

SOFTWARE AND DATA FOR CIRCULAR ECONOMY ASSESSMENT

Franco Donati

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1 INTRODUCTION

1.1 CIRCULAR ECONOMY

In the current economy, we take materials from the Earth, transform them into products, use these products and then discard them as waste. This linear model is currently the main way of utility and value creation. The environment is only perceived as a provider of primary resources, and a place that should absorb waste and emissions. However, everything is an input to something else in a virtually closed system such as our planet. Considering the economy as a way to only produce utility and value is bound to result in overexploitation of resources, exceeding planetary boundaries and therefore threatening our natural living support system (Rockström et al., 2009).

The circular economy (CE) aims to mitigate this threat by considering the limitedness of our resources and the limited ability of the environment to work as a sink for waste and emissions from our industrial system. It promotes the use of resources in closed loops (e.g., re-use and recycling) which also implies the adoption of renewable resources extracted at a sustainable level, all the while ideally eliminating the use of exhaustible ones (Pearce et al., 1990, Chapter 2). This requires technological, organizational and policy changes aiming at the sustainable management of resources. Producer responsibility, servitization, business models innovation, sustainable consumption, eco-industrial parks, are among the many approaches that support a reduction of resource consumption and keep materials in closed loops (Ghisellini et al., 2016; Kirchherr et al., 2017b; Potting et al., 2016). Several scholars and organizations have tried to provide a clear definition of a circular economy (Calisto Friant et al., 2020; EMF, 2015b; Kirchherr et al., 2017b). Kirchherr et al. (2017) considered no less than 114 definitions, from which they suggested to define a circular economy as:

"An economic system that replaces end-of-life concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes. It operates at the micro-

level (products, companies, consumers), meso-level (eco-industrial parks) and macro-level (city, region, nation and beyond), with the aim to accomplish sustainable development, thus simultaneously creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations. It is enabled by novel business models and responsible consumers."

In addition to the Micro-Meso-Macro subdivision which was originally offered by Ghisellini et al. (2016), strategies to realise a CE strategies can be grouped in different categories (Aguilar-Hernandez et al., 2018a; EMF, 2012; Potting et al., 2016). One of these consists of the so-called R principles that support a circular use of products, their components and materials (see Figure 1). Another is the so-called 'butterfly diagram' developed by the Ellen MacArthur Foundation (EMF, 2012), see Figure 2. Later, the EMF and McKinsey developed the so-called ReSOLVE framework as a tool for business and government to implement CE strategies (EMF, 2015a):

- REgeneration: technological and resource use changes that aim at retaining utility of resources
- Share: the sharing of resource and products
- Optimize: increase efficiency, remove waste, and leverage big data, automation and remote sensing and steering
- Loop: employing technologies and changing organization around the recovery and reuse of resources that have reached their end of life
- Virtualize: dematerializing products and services by offering them through a digital alternative
- Exchange: substituting material and technologies for more sustainable alternatives

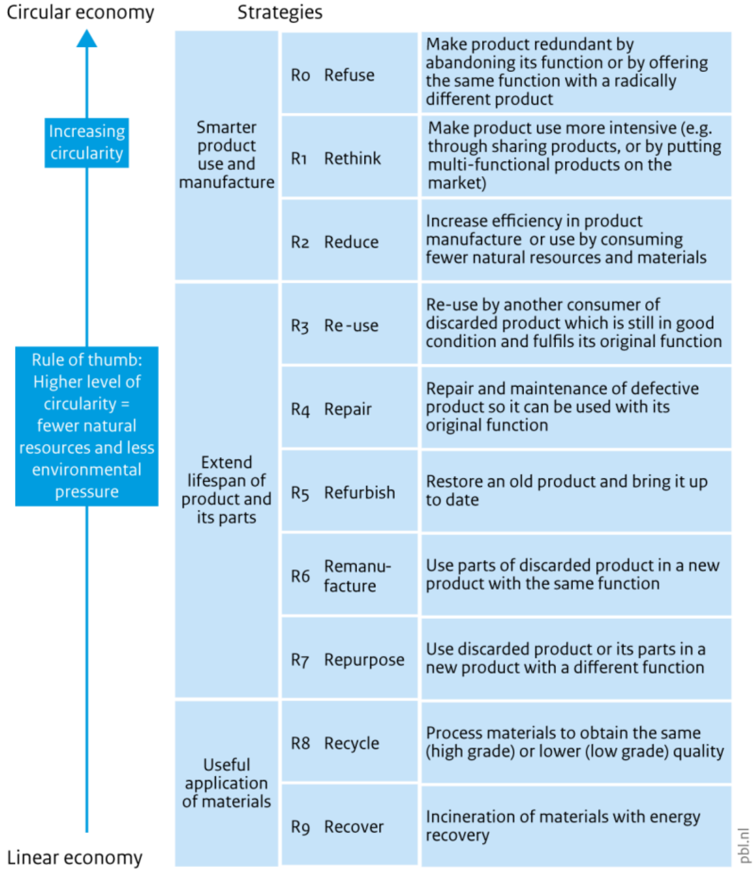

Figure 1: R Strategies (Potting et al., 2016)

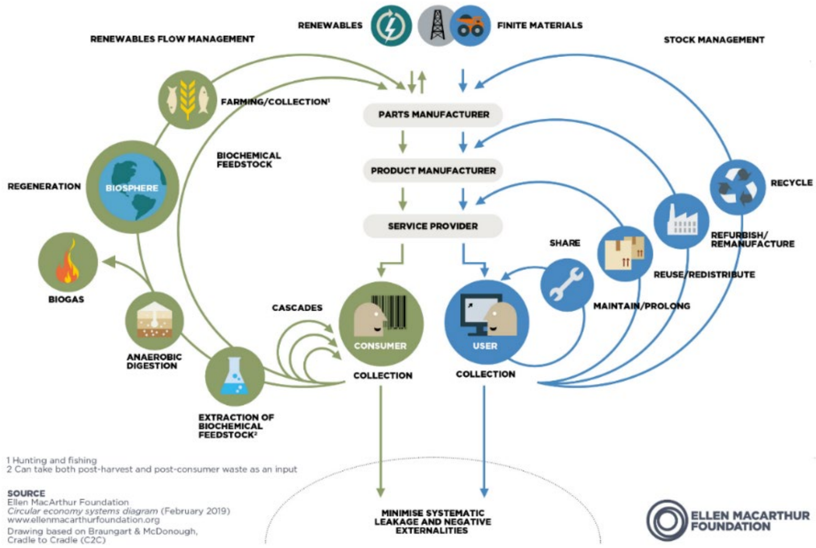

Figure 2: Circular Economy Butterfly Diagram (EMF, 2015b)

The main ambition of this thesis is to contribute to the development of assessment methods that analyze the economic, social, and environmental implications of CE strategies. This implies that an unambiguous grouping of CE strategies is required that can be used easily in socio-economic and environmental assessment methods. However, some of the groupings presented above leave room for unclarity. For example, does recycling fall under regeneration or loop? In order to assess the potential impacts of CE strategies, it is important to have a clear framework that is suitable for use in combination with assessment tools such as Environmental Input Output (IO) models – as explained in section 1.2 tools widely used by the scientific community to asses economic, social and environmental implications of sustainability policies. Through analysis of macro-economic studies on CE, Aguilar-Hernandez et al. (2018) showed that the following classification of CE strategies, essentially an aggregate of classifications mentioned before, is well suited to use in assessments based on IO and related models:

- Resource efficiency
- Closing supply chain loops
- Product life extension
- Residual waste management

The CE is in essence an aggregate of changes in technologies and policies in specific sectors and in the relationship among sectors aimed at reducing resource consumption and generating value. These changes by themselves may bring about marginal gains macro-economically but their compound effect in the avoidance of environmental pressures and socio-economic value generation could be substantial. In other words, the macro-level effects are the result of aggregate use and effects of micro and meso-level strategies. To assess the environmental and socio-economic performance of the CE, modelers have two choices: 1) Model aggregate effects of the strategies in production and consumption (e.g., global reduction of material consumption by 30% across all sectors); or 2) model detailed changes to simulate specific interventions (e.g., diversion of scrap metal from manufacturing). In the following section we discuss different modelling approaches that can analyze the social, economic and/or environmental impacts of CE strategies and interventions.

1.2 MODELS FOR CIRCULAR ECONOMY ASSESSMENT

To understand the social, environmental and economic effects of CE policies, the expected changes in the economy and technology need to be modelled. Different analytical tools are available for such modelling. Each of them has its particular strengths and weakness in capturing subtleties of the strategies as highlighted in the former section (e.g. Donati et al. (2021) and Walzberg et al. (2021)). In other words, questions concerning the modelling of circular economy can be answered through a variety of analytical tools from various fields of sustainability from industrial ecology to economics and complexity science.

Analytical tools can be divided depending on their focus of application: micro, meso and macro levels. The micro-level concerns models that focus on individual product systems (e.g., a consumer good) or specific technologies (e.g., industrial water filtration systems). The meso level may concern how a given supply chain is organized (e.g., industrial relationships, their inputs and outputs for the production of a given consumer good) or a given bulk material transformed across multiple industries and regions from extraction to disposal (e.g., copper extracted in a region and how its use in different equipment. The macro level mainly concerns how entire economies are represented and organized in their complexity, showing who is consuming or producing products and providing services, their requirements and effects (e.g., how all products are manufactured and consumed in Italy or globally). In the field of Industrial ecology, Life Cycle Assessment (LCA), Material Flow Analysis (MFA), and Environmentally Extended Input-Output Analysis (EEIOA) are key methods to assess the impacts of CE interventions (Aguilar-Hernandez, Dias Rodrigues, et al., 2021; Haas et al., 2015; Sassanelli et al., 2019).

LCA focuses on "compilation and evaluation of the inputs outputs and potential environmental impacts of a product system throughout its life cycle" (ISO, 2006). LCA is regulated by ISO 14040 and is divided in 4 phases: 1) Goal and scope definition; 2) Inventory Analysis; 3) Impact assessment; 4) Interpretation. In particular, in LCA the inputs and outputs of technological processes (i.e., activities) are modelled. Activities are connected to each other by their inputs and outputs. Aggregates of activities form lifecycle stages, from the extraction to the end-of-life (EOL) (recycle/waste management). Flows that enter and exit unit processes are divided into economic and environmental flows. Economic flows connect activities and concern intermediate and final products and services of positive, negative or zero economic value. Environmental interventions are chemical, physical or biological anthropic interferences with the natural environment such as the extraction of resources or the emission of pollutants into nature. These quantified flows are inputs and outputs to the environment relative to the primary function(s) (i.e., functional unit) satisfied by a product system (Guinée, 2001). Given the high level of detail of discerning unit processes in LCA, it usually applied at individual product level. For this reason LCA has been promoted as an ideal tool for circular economy assessment. First, it is a recognized, standardized and scientifically based methodology in the field of sustainability (Pena et al., 2021). But second, it is a tool capable of looking in high detail at product specific CE strategies (e.g. re-use of components from end-of-life copiers). Therefore, many CE studies that focus at the micro and meso level have employed LCA (Sassanelli et al., 2019; Walzberg et al., 2021). Examples include the assessment of biobased products (Dahiya et al., 2020), closing material loops for metal packaging (Niero & Olsen, 2016), novel business models for consumer products (Hoffmann et al., 2020; Sigüenza et al., 2021), and closing loops in the construction sector (van Stijn et al., 2021). While LCA is very well suited to analyze environmental benefits of CE product systems, the foreground activities concern only one product system at a time and it typically requires substantial human and time resources to collect and compile the necessary data (i.e., life cycle inventories) for each analysis. Additionally, for LCA to provide insights other than environmental impacts, more data or methods hybridization are required to gain insights on social and economic impacts.

Also MFA has been used for circular economy assessments. It is an appropriate tool to follow materials and substances throughout their different life cycle stages from extraction to disposal, or through different regions (Ayres & Ayres, 2002b). Similarly to LCA, MFA traces the inputs and outputs through transformation processes but with a special focus on the material balance of a single or bulk material and the creation and development of its stocks through a region or industrial system (Ayres & Ayres, 2002b, Chapter 8; Ayres & Simonis, 1995). This makes MFA a suitable tool for the analysis of CE at the meso-level. The inclusion of stocks is important, as it help with forecasting at which moment end-of-life materials will become available for re-use and recycling in the future provided that average lifespan of products is known. For example, Millette et al. (2019) used MFA to investigate plastic management solutions to implement the CE in Trinidad and Tobago and Dong et al. (2020) assessed future scenarios of copper demand in China and how circular economy policies would effect demand.

So, while LCA and MFA are great for detailed CE analyses at product and material level, they do not cover the whole economy. They also look at the economy in physical terms, but do not include information on e.g. jobs, added value, or costs. LCA and MFA hence can provide excellent environmental impact analyses, but not economic or social analyses. EEIOA is more capable of covering social, environmental and economic impacts of CE interventions with a reasonable product and geographic detail. The basics of EEIOA are described in Box 1 (Leontief, 1941, 1970a). An IO table divides the economy of a country in a number of sectors (or products) and their inputs (e.g., services, goods and employment) required for the supply of goods and services to other industries and final consumers. The difference between the consumption of all products and services by an industry and its output is value added (i.e., .e. the sum of wages, taxes and subsidies and profit). The sum of all value added by industry defines the Gross Domestic Product (GDP). The IO table can further be 'extended' with environmental information such as the emissions and primary resource extraction of each sector, leading to an Environmentally Extended IO (EE IO). But there can also be other extensions, such as the employment numbers per sector. When IO tables of multiple countries are combined together connecting them through their trade relationships, this results in a multi-regional IO system, which in principle can cover all countries and all sectors in the global economy (i.e., Global MRIO). If a MRIO system, global or otherwise, comes with a set of environmental extensions, it is referred to as a MR EEIO system.

Box 1.1: Multi-regional Environmentally Extended Input-Output Analysis

Environmentally Extended Input-Output (EEIO) analysis (Leontief, 1970; Suh, 2009) is based on Input-Output (IO) analysis (Leontief, 1951; Miller and Blair, 2009) and deals with the quantification of environmental pressures that take place along the supply chain of goods and services, by assuming that production structure remains fixed. The basic Leontief demand-driven model can be framed such that a stimulus vector of final demand leads to a set of emissions occurring in each production sector as:

$$\mathbf{r} = \mathrm{diag}(\mathbf{b})(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} \tag{1}$$

In the preceding expression $\mathbf{r}$ is the column vector of emissions occurring in each production sector (the response variable) and $\mathbf{y}$ is the column vector of final demand of products delivered by each sector (the control variable). The parameters of the model are the column vector $\mathbf{b}$ of environmental intensities (environmental pressure per unit of economic output) and $\mathbf{A}$ is a matrix of technical coefficients (i.e., direct requirements matrix) whose entry ij is the volume of inputs from sector i that are required to generate one unit of output of sector j.

diag stands for diagonal matrix and $\mathbf{I}$ is the identity matrix. The technical coefficient matrix is calculated as $\mathbf{A} = \mathbf{Z}\,\mathrm{diag}(\mathbf{x})^{-1}$, where $\mathbf{Z}$ is the matrix of inter-industry transactions and $\mathbf{x}$ is the column vector of total output of each sector, $\mathbf{x} = \mathbf{Z}\,\mathbf{i} + \mathbf{Y}\,\mathbf{i}$, the row sum of $\mathbf{Z}$ and $\mathbf{Y}$, where the latter is a matrix whose columns represent the final demand of different consumption categories (e.g., households, government, investment), and $\mathbf{i}$ is a vector column of ones.

Equation 1 can also be expressed in multi-regional form:

$$\begin{matrix} \mathrm{r}_1 \\ \mathrm{r}_2 \\ \mathrm{r}_3 \end{matrix} = \begin{pmatrix} \boldsymbol{B}_{11} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{B}_{22} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{B}_{33} \end{pmatrix} \cdot \left(\boldsymbol{I} - \begin{pmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} & \boldsymbol{A}_{13} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} & \boldsymbol{A}_{23} \\ \boldsymbol{A}_{31} & \boldsymbol{A}_{32} & \boldsymbol{A}_{33} \end{pmatrix} \right)^{-1} \cdot \begin{pmatrix} \boldsymbol{Y}_{11} & \boldsymbol{Y}_{12} & \boldsymbol{Y}_{13} \\ \boldsymbol{Y}_{21} & \boldsymbol{Y}_{22} & \boldsymbol{Y}_{23} \\ \boldsymbol{Y}_{31} & \boldsymbol{Y}_{32} & \boldsymbol{Y}_{33} \end{pmatrix} \cdot \boldsymbol{i}$$

Here the subscript numbers in each matrix transaction indicates the region coordinates and the type of transaction. For instance, $\mathbf{A}_{11}$ indicates the direct requirement coefficient for the domestic production of region 1, while $\mathbf{A}_{12}$ is the direct requirement coefficient for production that is exported by region 1 to region 2. In other words, values on the diagonal of the $\mathbf{A}$ matrix represent domestic consumption and production, while transactions off the diagonal are import and exports to other regions.

MR EEIO databases (see box 1.2) contain data concerning global economic relationships (e.g., trade) and for each country and sector environmental extensions from extraction to greenhouse gas emissions. For this reason, it is often employed in the analysis of circular economy policies at the macro-economic level (Aguilar-Hernandez, Dias Rodrigues, et al., 2021; Walzberg et al., 2021). For example, Wijkman et al. (2015) explored the employment and GHG impacts of CE in the European Union economy, and Wiebe et al. (2018) investigated the global impacts of circular economy interventions to the year 2030. The advantage of EEIOA over e.g. LCA and MFA for the analysis of CE policies is that it covers the whole economy and covers next to environmental also socio-economic data such as employment, value added and taxation to name a few. The Leontief model makes it easier to process such large amount of data, on the other hand it limits modelers to static analysis. However, due to limits in computational power, there is a trade-off between data resolution and complexity of models. In fact, typically the more complex the interrelationship in the model the lower the data resolution. MR EEIO offers an effective trade-off between capturing many details about the economy and the environment while also being computationally and mathematically accessible by most analysts. Tools like Computable General Equilibrium (CGE) models capture more complex economic dynamics, but usually at the expense of data resolution. Given the fact that CE strategies can be highly product specific while we at the same time wanted to cover social and economic aspects, and also wanted to capture global trade-offs of CE policies, we decided upon using MR EEIO as the main tool in this thesis.

Box 1.2: Data for Multi-regional Environmentally Extended Input-Output

EE IO data is in many countries based on official data from the well-established System of National Accounts used by National Statistical Institutes (EUROSTAT, 2008). The accounts offer a rich variety of data which includes sectoral production statistics, households surveys, employment and in many cases environmental and waste data that may be collected by geological and environmental agencies present on the national territory (Beutel et al., 2018; EUROSTAT, 2008). Such an EE IO dataset allows to investigate socio-economic and environmental impacts of groups of products, materials, and sectors in an interrelated fashion. In essence, an EE IO dataset allows calculating how e.g., a change in final demand of a specific product leads to changes in production volumes in all economic sectors – and hence changes in emissions and resource extraction, value added creation, and job numbers (see Box 1.1). In most cases, IO databases are collected and disseminated by National Statistical Offices (NSOs) and supranational organizations such as European Statistical Office (EUROSTAT, 2022b), the Organisation for Economic Co-operation and Development (OECD, 2022) or the Asian Development Bank (ADB, 2022). Additionally, the databases provided by NSOs are made only for the country in which the NSO is based, and often have only a limited number of environmental extensions available. Since in many countries imports and exports play significant role for the Gross Domestic Product (GDP), it is important to include the supply chains to and from a country. This can be done by linking country IO tables via international trade, which gives a so-called multi-regional IO database. Making such MRIOs is complex: individual country IOTs must be brought into the same classification, trade data have to be added, etc. Since the total exports in all country IO tables differs from total exports, imbalances must be solved which inevitably implies adjusting national IO tables. For this reason multi-regional (MR) EEIO databases such as EXIOBASE (Stadler et al. 2018), EORA (Lenzen et al., 2013), GTAP (Peters et al., 2011) and others have been largely developed by the scientific community, in some cases adding sector detail in environmentally relevant sectors (Stadler, Wood, Bulavskaya, Södersten, Simas, Schmidt, Usubiaga, Acosta-Fernández, Kuenen, Bruckner, Giljum, Lutter, Merciai, Schmidt, Theurl, Plutzar, Kastner, Eisenmenger, Erb, Koning, et al., 2018).

1.3 SOFTWARE AND DATA FOR CIRCULAR ECONOMY ASSESSMENT

The models described in the previous sections rely on software and data to assess the potential effects of the CE, which are so complex they usually only can be applied by scientists and specialist practitioners. The analysis in the previous section indicates that tools and models for CE analyses are available, however, virtually all the analytical tools mentioned (LCA, MFA, EEIO) need involvement of highly skilled experts and substantial time investment. For policy makers this is a drawback. Similar to e.g. carbon footprint calculators that show how consumption changes could lower carbon emissions (Mulrow et al., 2019), it would be ideal if a simple to use scenario tool would be available, in which they could select CE scenarios for products and get a first impression of economic, environmental and social implications. However, in most cases analytical tools that could be used to create CE scenarios are either specifically developed for users with a programming background and/or available under paid licenses. This is an issue which affects accessibility of data of public interest concerning the economy and the environment, as well as limiting transparency and replicability of studies as implementations of scenarios may vary. For this purpose, easy to use software tools such as web applications are of great importance to ensure rapid and replicable development of scenarios, and access to the environmental and economic insights needed to promote the CE and sustainability at a large.

Data availability also plays a fundamental role in CE assessment as it can enhance models and validity of outcomes (Lahcen et al., 2022).However, due to the labor intensity of data collection and handling, there are challenges in timeliness and detail of data concerning products, activities, environmental impacts. Such challenges result in several limitations depending on the model choice. For example, IO data discern at best only a few hundred sectors or product categories, and in practice often only a few dozen. Hence data on production systems is much more aggregated than it would be in LCA or MFA studies where thousands of detail processes may be available. Past experience has shown that even the most detailed, global EE IO databases compiled by the scientific community have significant drawbacks in relation to the needs of CE impact assessment (Aguilar-Hernandez, Deetman, et al., 2021):

- Low resolution of product categories (I.e., families of individual products that have different functions, and more important, require specific technical approaches to realizing CE)
- Expression of transactions between industries in economic instead of physical terms. This is particularly important for CE modelling, since end-of-life components or waste have no, low and highly variable value so that economic value does not represent well physical flows.
- No or limited detail for specific re-use and waste management sectors, while they are the ones most relevant for CE
- No data on in use material stocks, while these determine future outflows of end-of-life products

In brief, there is also a need for an expanded and systemic data collection efforts for CE. This work needs to realize more detail in EEIO data and present sectors involved in re-use and recycling of products in physical terms. A common practice in the EEIO community for the development of databases with high product resolution is to gather LCA data such as Life Cycle Inventories. LCI data can be obtained from multiple sources, and each providing a different level of accuracy (Parvatker & Eckelman, 2019). For instance, while plant data provides the maximum level of accuracy, in many cases, this data is not accessible due to security and intellectual property concerns. Therefore, simulation tools are the next best option in lack of confidential industrial data (Parvatker & Eckelman, 2019). In this thesis we make a distinction between simulation software created to solve one or a limited number of specific problems, and standardized software tools such as Computer Aided Technologies (CAx). The former typically focuses on only specific applications and analysis, it may vary in quality as it may be developed by software developers with limited resources, and as a result the number of users may be smaller. CAx, on the other hand, generally enjoy a high level of standardization and support, general feature richness and a large user-base. This is software that is already broadly used by product developers and engineers.

In this thesis we focus on the former as replicability of results and standardization of practices is of great importance to create a reliable data pipeline for continuous data collection. However, simulating entire products and their production processes is also a labor intensive effort. Techniques from Artificial Intelligence and the use of digital technologies may be needed to promote automation in data retrieval and in estimation of missing data. Such practices in connection with the broad use of data collection efforts through digital technologies should then become pervasive systems of data collection for the fields of CE and Industrial Ecology.

1.4 Problem statement and research questions

In the previous section, we saw a number of issues. Firstly, we found that EEIO in principle is a good tool that can help to assess economic, social and environmental implications of CE strategies. Such assessments usually are supported by first analyzing the priority 'hot spots' of environmental pressures in a system, and then analyzing how CE interventions may reduce them but, secondly, we also found that methods like MR EEIO analysis require a high level of skills to make such scenarios, leading to the suggestion that a CE scenario tool may help policy makers and practitioners easier to gain insight in good CE options, and hence, CE dissemination. Thirdly, while MR EEIO maybe a very promising tool for CE analyses, it is likely that in future more detailed data will be required than what is currently available in existing MR EEIO databases. Since data collection is usually labor intensive, this leads to the question whether simulation tools, artificial intelligence methods and digital technologies can support these efforts.

Based on this problem statement, the main research question and related sub-questions are articulated in this way:

How can we facilitate and promote the environmental, social and economic assessment of Circular Economy interventions at the macro level?

- Sub-question 1 – How can MR EEIO be used for priority setting of CE interventions?
- Sub-question 2 – How can CE strategies be modelled with MR EEIO?
- Sub-question 3 – How can we create a user-friendly interface for modelling CE strategies with MR EEIO, easily accessible for non-specialists?

- Sub-question 4 - How can we use Computer-Aided Technologies (CAx) and Artificial Intelligence (AI) methods to increase data availability for the analysis of CE?
- Sub-question 5 - How can the IE community position itself with regards to AI and digital technologies to better support sustainability and CE assessment?

1.5 Structure of the thesis

In relation to the questions above, this thesis is structured as follows.

Chapter 2 studies the environmental and economic impacts of final consumption of agricultural production due to imported consumption. The study is used to understand how MR EEIO can be used to support policy making and to highlight hot spots related to the impacts of international food supply chain.

Chapter 3 concerns the development of software and methods for standardized and replicable CE scenario making in MR EEIO. A case study is also presented on the global environmental and socio-economic impacts of the implementation of CE strategies.

Chapter 4 develops a web-application with the intent to facilitate low-threshold access to and use of MR EEIO data, in the form of a CE scenario tool that offers easy to interpret outcomes and visualizations.

Chapter 5 addresses the issues of data availability and resolution in MR EEIO. By performing a systematic literature review we show how computer-aided technologies and artificial intelligence methods may be used to generate and estimate data useful for LCIs, which in turn could be used to enrich LCI and MR EEIO databases.

Chapter 6 presents a vision of some key experts for the industrial ecology and circular economy communities on how to improve data collection practices by leveraging digital technologies (DT) and artificial intelligence (AI) methods. It discusses challenges and opportunities in the use of AI and DTs and presents recommendations for future steps.

Finally, chapter 7 provides answers to the research questions posed in the former sections, provides overall conclusions, and reflects on topics for further research and policy implications.

REFERENCES

ADB. (2022). *Supply and Use Tables (SUT) | ADB Data Library | Asian Development Bank.* https://data.adb.org/taxonomy/term/132

Aguilar-Hernandez, G. A., Deetman, S., Merciai, S., Rodrigues, J. F. D., & Tukker, A. (2021). Global distribution of material inflows to in-use stocks in 2011 and its implications for a circularity transition. *Journal of Industrial Ecology, 25*(6), 1447–1461. https://doi.org/10.1111/jiec.13179

Aguilar-Hernandez, G. A., Dias Rodrigues, J. F., & Tukker, A. (2021). Macroeconomic, social and environmental impacts of a circular economy up to 2050: A meta-analysis of prospective studies. *Journal of Cleaner Production, 278*, 123421. https://doi.org/10.1016/j.jclepro.2020.123421

Aguilar-Hernandez, G. A., Sigüenza-Sanchez, C. P. C. P. C. P., Donati, F., Rodrigues, J. F. D. J. F. D., & Tukker, A. (2018). Assessing circularity interventions: A review of EEIOA-based studies. *Journal of Economic Structures, 7*(1), 14. https://doi.org/10.1186/s40008-018-0113-3

Ayres, R. U., & Ayres, L. (2002). *A Handbook of Industrial Ecology.* Edward Elgar Publishing.

Ayres, R. U., & Simonis, U. E. (1995). Industrial metabolism: Restructuring for sustainable development. *Fuel and Energy Abstracts, 4*(36), 275.

Beutel, J., Rueda-Cantuche, J. M., Inomata, S., & Amores, A. F. (2018). *Handbook on Supply, Use and Input-Output Tables with Extensions and Applications*. United Nations.

Calisto Friant, M., Vermeulen, W. J. V., & Salomone, R. (2020). A typology of circular economy discourses: Navigating the diverse visions of a contested paradigm. *Resources, Conservation and Recycling, 161,* 104917. https://doi.org/10.1016/j.resconrec.2020.104917

Dahiya, S., Katakojwala, R., Ramakrishna, S., & Mohan, S. V. (2020). Biobased Products and Life Cycle Assessment in the Context of Circular Economy and Sustainability. *Materials Circular Economy, 2*(1), 7. https://doi.org/10.1007/s42824-020-00007-x

Donati, F., Merciai, S., Deetman, S., Aguillar-Hernandez, G., Rietveld, W., Bastein, A. G. T. M., Boonman, H. J., Melo, F., & Hauck, M. (2021). *Learning from circular economy relevant modelling approaches*. TNO. https://repository.tno.nl/islandora/object/uuid%3A84ee54eb-311e-4246-aae3-07516eb3faf3

Dong, D., Espinoza, L. A. T., Loibl, A., Pfaff, M., Tukker, A., & Van der Voet, E. (2020). Scenarios for anthropogenic copper demand and supply in China: Implications of a scrap import ban and a circular economy transition. *Resources, Conservation and Recycling, 161*, 104943. https://doi.org/10.1016/j.resconrec.2020.104943

EMF. (2012). *Towards the Circular Economy. Economic and business rationals for an accelerated transition.* Greener Management International, 2, 1–96.

EMF. (2015a). *Growth within: A circular economy vision for a competitive europe. Ellen MacArthur Foundation, 100*. https://doi.org/Article

EMF. (2015b). *Towards a Circular Economy: Business Rationale for an Accelerated Transition. In Greener Management International*. https://doi.org/2012-04-03

EUROSTAT. (2008). *Eurostat Manual of Supply, Use and Input-Output Tables. In Methodologies and working papers*, Economy and finance. http://ec.europa.eu/eurostat

EUROSTAT. (2022). *Data—ESA supply, use and input-output tables—Eurostat*. https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production, 114*, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007

Guinée, J. (2001). Handbook on life cycle assessment—Operational guide to the ISO standards. In *International Journal of Life Cycle Assessment.* https://doi.org/10.1007/BF02978784

Haas, W., Krausmann, F., Wiedenhofer, D., & Heinz, M. (2015). How Circular is the Global Economy?: An Assessment of Material Flows, Waste Production, and Recycling in the European Union and the World in 2005. *Journal of Industrial Ecology, 19*(5), 765–777. https://doi.org/10.1111/jiec.12244

Hoffmann, B. S., de Simone Morais, J., & Teodoro, P. F. (2020). Life cycle assessment of innovative circular business models for modern cloth diapers. *Journal of Cleaner Production, 249*, 119364. https://doi.org/10.1016/j.jclepro.2019.119364

ISO. (2006). *14040: Environmental management–life cycle assessment—Principles and framework*. International Organization for Standardization.

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling, 127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Lahcen, B., Eyckmans, J., Rousseau, S., Dams, Y., & Brusselaers, J. (2022). Modelling the circular economy: Introducing a supply chain equilibrium approach. *Ecological Economics, 197,* 107451. https://doi.org/10.1016/j.ecolecon.2022.107451

Lenzen, M., Moran, D., Kanemoto, K., & Geschke, A. (2013). Building Eora: A Global Multi-Region Input–Output Database at High Country and Sector Resolution. *Economic Systems Research, 25*(1), 20–49. https://doi.org/10.1080/09535314.2013.769938

Leontief, W. (1941). *The structure of American economy, 1919-1929: An empirical application of equilibrium analysis*. Harvard University Press.

Leontief, W. (1970). Environmental Repercussions and the Economic Structure: An Input-Output Approach. *The Review of Economics and Statistics, 52*(3), 262–271. https://doi.org/10.2307/1926294

Millette, S., Williams, E., & Hull, C. E. (2019). Materials flow analysis in support of circular economy development: Plastics in Trinidad and Tobago. *Resources, Conservation and Recycling, 150,* 104436. https://doi.org/10.1016/j.resconrec.2019.104436

Mulrow, J., Machaj, K., Deanes, J., & Derrible, S. (2019). The state of carbon footprint calculators: An evaluation of calculator design and user interaction features. *Sustainable Production and Consumption, 18*, 33–40. https://doi.org/10.1016/j.spc.2018.12.001

Niero, M., & Olsen, S. I. (2016). Circular economy: To be or not to be in a closed product loop? A Life Cycle Assessment of aluminium cans with inclusion of alloying elements. *Resources, Conservation and Recycling, 114,* 18–31. https://doi.org/10.1016/j.resconrec.2016.06.023

OECD. (2022). *Supply and Use Tables, database—OECD.* https://www.oecd.org/sdd/na/supply-and-use-tables-database.htm

Parvatker, A. G., & Eckelman, M. J. (2019). Comparative Evaluation of Chemical Life Cycle Inventory Generation Methods and Implications for Life Cycle Assessment Results. *ACS Sustainable Chemistry and Engineering.* https://doi.org/10.1021/acssuschemeng.8b03656

Pearce, D. W., Turner, R. K., & Turner, P. R. K. (1990). *Economics of Natural Resources and the Environment*. JHU Press.

Pena, C., Civit, B., Gallego-Schmid, A., Druckman, A., Caldeira-Pires, A., Weidema, B., Mieras, E., Wang, F., Fava, J., Canals, L. M. i, Cordella, M., Arbuckle, P., Valdivia, S., Fallaha, S., & Motta, W. (2021). Using life cycle assessment to achieve a circular economy. *International Journal of Life Cycle Assessment, 26*(2), 215–220. https://doi.org/10.1007/s11367-020-01856-z

Peters, G. P., Andrew, R., & Lennox, J. (2011). Constructing an Environmentally-Extended Multi-Regional Input–Output Table Using the Gtap Database. *Economic Systems Research, 23*(2), 131–152. https://doi.org/10.1080/09535314.2011.563234

Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2016). *Circulaire economie: Innovatie meten in de keten. 41.*

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., … Foley, J. A. (2009). A safe operating space for humanity. *Nature, 461*(7263), Article 7263. https://doi.org/10.1038/461472a

Sassanelli, C., Rosa, P., Rocca, R., & Terzi, S. (2019). Circular economy performance assessment methods: A systematic literature review. *Journal of Cleaner Production, 229*, 440–453. https://doi.org/10.1016/j.jclepro.2019.05.019

Sigüenza, C. P., Cucurachi, S., & Tukker, A. (2021). Circular business models of washing machines in the Netherlands: Material and climate change implications toward 2050. *Sustainable Production and Consumption, 26*, 1084–1098. https://doi.org/10.1016/j.spc.2021.01.011

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J. H., Theurl, M. C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., … Tukker, A. (2018). EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *Journal of Industrial Ecology, 22*(3), 502–515. https://doi.org/10.1111/jiec.12715

van Stijn, A., Malabi Eberhardt, L. C., Wouterszoon Jansen, B., & Meijer, A. (2021). A Circular Economy Life Cycle Assessment (CE-LCA) model for building components. Resources, *Conservation and Recycling, 174,* 105683. https://doi.org/10.1016/j.resconrec.2021.105683

Walzberg, J., Lonca, G., Hanes, R. J., Eberle, A. L., Carpenter, A., & Heath, G. A. (2021). Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review. *Frontiers in Sustainability, 1*. https://www.frontiersin.org/articles/10.3389/frsus.2020.620047

Wiebe, K. S., Bjelle, E. L., Többen, J., & Wood, R. (2018). Implementing exogenous scenarios in a global MRIO model for the estimation of future environmental footprints. *Journal of Economic Structures, 7*(1). https://doi.org/10.1186/s40008-018-0118-y

Wijkman, A., Skånberg, K., & Berglund, M. (2015). *The Circular Economy and Benefits for Society*. The club of Rome.

2 ENVIRONMENTAL PRESSURES AND VALUE ADDED RELATED TO IMPORTS AND EXPORTS OF THE DUTCH AGRICULTURAL SECTOR

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ABSTRACT
This study shows the environmental impacts and economic performance due to agricultural trade through The Netherlands. Using the demand-driven input–output model and the database EXIOBASE (2011), we first analysed the environmental impacts and value added directly generated abroad by the agricultural sector through imported final consumption in The Netherlands; we then compared the environmental impacts and value added generated in The Netherlands by the agricultural sector due to exports to other countries. The results show that the Dutch consumption of imported agricultural products had significant greenhouse gas emissions of 19,386 kt CO_2-eq, land use of 280,525 km^2 and water consumption of 50,373 M.m^3, while impacts in The Netherlands due to agricultural exports amounted, respectively, to 13,022 kt CO_2-eq, 9282 km^2 and 3339 M.m^3. At the same time, we found that Dutch agricultural production had a higher value added to pressure ratio than abroad. These differences highlight the great dependency of Dutch final consumption on foreign natural resources, a significant trade imbalance for environmental impacts with relatively smaller economic benefits for countries exporting to The Netherlands. With these results, we suggest that it is of great importance that sustainability policies for the agricultural sector not only address environmental impacts domestically but also impacts and value creation abroad.

KEYWORDS
Agriculture; Trade; Environmental impacts; Economic performance

2.1 INTRODUCTION

The Dutch agricultural sector drives environmental pressures beyond national borders—for example, due to the import of feed for Dutch livestock. Conversely, export countries that import Dutch agricultural produce also drive emissions and impacts in The Netherlands. With an agricultural export of EUR 95.6 billion (over 10% of Gross Domestic Product, GDP), The Netherlands is, after the US, the largest exporter of agricultural products globally. Hence, such 'impacts embodied in trade' are likely to be significant. There is no shortage of studies that have analyzed the (global) environmental footprint of diets (Behrens et al., 2016; Eker et al., 2019; Marques et al., 2019; Tukker et al., 2011; Westhoek et al., 2014). Moreover, the footprints of diets in The Netherlands have been researched, often as part of general analyses of the environmental footprints of consumption (de Vries & te Riele, 2006; Ivanova et al., 2016; Nijdam et al., 2005; van Dooren et al., 2014). Additionally, studies have also been conducted on environmental justice and the impacts of agricultural production and consumption, and indicated how global land use and biodiversity loss are driven through trade (Sun et al., 2022).

However, to our knowledge, there has been no study that has used the Dutch agricultural sector as an entry point, as opposed to the widely used approach of analyzing the global impacts of (Dutch) final consumption of food. Given the crucial role that the Dutch agricultural sector has in imports, exports and value added creation of The Netherlands, it is interesting to see how this sector drives the global footprints and value added of its imports, and how agricultural exports drive environmental and economic impacts in The Netherlands.

The objective of this study is to quantify the environmental impacts and value added created through trade from and to The Netherlands in the agricultural sector. For this purpose, we created a dashboard (see Supplementary Information, Annex I) that can be used to further investigate various types of indicators also beyond the ones discussed in this study. A summary of the results given in this article, together with their visualizations, is also provided in the Supplementary Information, Annex II.

This article addresses the following research questions:

- What are the environmental impacts and economic benefits in The Netherlands caused by Dutch agricultural exports for final consumption abroad?
- What are the environmental impacts and economic benefits in countries from which The Netherlands imports agricultural products for its final consumption?

2.2 MATERIALS AND METHODS

2.2.1 General Methods and Data

In our analysis, we investigated the direct environmental pressure and value added created per sector and per country through trade to and from The Netherlands. A footprint analysis of the total imports and exports of The Netherlands was performed, followed by a contribution analysis for sectors and regions. There are various approaches to analyzing the environmental impacts of trade and of activities by an economic sector in a specific country. For example, the coefficient approach is widely used to calculate impacts embodied in imports and exports (Hoekstra & van den Bergh, 2006; Moran et al., 2009). Such approaches use detailed import and export data from international trade databases (e.g., UN COMTRADE), in combination with pressure indicators such as liters of water or m^2 of land required to produce the imported or exported products. The disadvantage of such an approach is that it does not cover the full value chains globally. For instance, imported products can contain components made elsewhere, such as in the exporting country. However, these data miss the imports and exports of services, and the indirect embodied impacts related to them. Therefore, multi-regional input–output approaches (MRIO) have become the method of choice for footprint analyses. MRIOs have as a further advantage that they contain information on value added by sector, which allows for the combined calculations of environmental and economic aspects related to the imports and exports of products. For this reason, we decided to use the demand-driven IO model (Leontief, 1970a; Miller & Blair, 2009, p. 784) (Equation 1) as it allows us to follow transactions and impacts across the full value chain.

$$\mathrm{r} = \hat{\mathrm{b}}\mathrm{Ly} \tag{1}$$

Here, r is a vector of environmental extensions (e.g., GHG emissions, land use or water consumption) and which, in mrIO, can be subdivided into regional emissions associated with given products or sectors. $\hat{\mathrm{b}}$ is a diagonal matrix resulting from the diagonalization of a vector of environmental coefficients, L is the Leontief inverse and y is the final demand vector.

2.2.2 Data

MRIO data show countries' total economy, with production divided into sectors, and consumption divided into product (and service) groups. Each sector produces an output (e.g., wheat), which is represented in monetary terms. At the same time, sectors make use of (intermediate) products to produce their outputs (i.e., inputs). Furthermore, for each sector, one can identify the direct sector-specific primary resource extraction and emissions ('Environmental Extensions' or EE)—for instance, land use by the agricultural sector, or CO2 emissions by the energy sector. It is therefore possible to analyze how economies are interconnected. For instance, for the final demand of wheat by consumers in a given region, it is possible to analyze the contribution of other sectors across multiple regions to the production of wheat (e.g., motor vehicles from Germany used in agriculture in The Netherlands) and the environmental pressures exercised by those inputs (EUROSTAT, 2008; Miller & Blair, 2009, p. 784).

Our analysis makes use of EXIOBASE V3 for the year 2011, a global MRIO database. EXIOBASE is not the only global MRIO database available, but to the best of our knowledge, it is the only one that combines product details for the agricultural sector together with a large number of environmental extensions (Tukker & Dietzenbacher, 2013). EXIOBASE discerns more than 200 product categories and 48 countries/regions and includes around 40 types of emissions, material extraction, water use and land use by sector and region as environmental pressures. We used 2011 as the base year since, at the time that our calculation was performed, this was the latest year for which full data were available. Although this database probably is one of the most detailed in the world, import and exports in the same product category can include different products. For example, in the case of imports to The Netherlands, 'fruit' can consist of mangoes and avocados, while in the case of exports by The Netherlands, they can consist of apples. This of course means a limitation in our analysis.

2.2.3 Contribution Analysis

In this study, we analyzed greenhouse gas (GHG) emissions, land use and water consumption next to value added as the main indicators. The analysis was divided in two steps:

1. Imported final demand by The Netherlands from other countries: we calculated the country-wise footprint of all imports for Dutch final consumption and then analyzed the direct contribution of agricultural product categories;
2. Exported final demand by The Netherlands to other countries: we calculated the country-wise footprint of all exports from The Netherlands and then analyzed the direct contribution of agricultural production in The Netherlands.

The direct environmental impacts and value added created abroad due to the consumption of imported products for final demand are calculated by performing a contribution analysis on the vector resulting from the following equation:

$$\mathrm{r}_{reg\_a}^{imp} = \hat{\mathrm{b}}\mathrm{L}\mathrm{y}_{reg\_a}^{imp} \tag{2}$$

Where r^{imp} is a vector of environmental pressures (or value added) due to the consumption of imported products in region a. The contribution analysis is then performed by isolating the values in the vector r^{imp} associated with agricultural production in a given region. In other words,

$$\mathrm{r} = \mathrm{r}_{reg\_a}^{prod\_a} + \mathrm{r}_{reg\_a}^{prod\_b} + \cdots + \mathrm{r}_{reg_b}^{prod_a} + \mathrm{r}_{reg\_b}^{prod\_b} + \cdots + \mathrm{r}_{reg\_n}^{prod_n} \tag{3}$$

where r is a scalar of the total environmental pressure resulting from the sum of the direct environmental pressure due to the production of all products in all regions.

2.3 RESULTS

In the next three sections, we present results concerning GHG emissions, land use and water consumption, aimed at answering our research questions presented in the Introduction section of this work.

2.3.1 Greenhouse Gas Emissions

Climate change is set to disrupt many aspects of the Dutch economy and society (Ligtvoet, 2015). Disruptions also occur globally in the form of droughts, floods and other extreme weather events that effect the environment, society and its economic activities (Kron et al., 2019). Because of the increasing effects of climate change, it is important to know where emissions occur so that they can be mitigated through national and international policy efforts.

Emissions in Kiloton

Figure 1 shows a contribution analysis of the GHG emissions due to Dutch final demand import and export. From Figure 1, we see that the total GHG emissions in The Netherlands due to the Dutch agricultural final demand export amount to 13,022 kt CO_2-eq. Moreover, 74% of these emissions are due to industries related to animal farming, while the remaining 26% are connected to other agricultural and forestry products. In particular, 48% (6281 kt CO_2-eq) of the total emissions is due to raw milk production; 16% (2043 kt CO_2-eq) to vegetables and fruits, and nuts; 11% (1395 kt CO_2-eq) to cattle; 8% (1007 kt CO_2-eq) to pigs; 6% (781 kt CO_2-eq) to poultry; and 12% (1517 kt CO_2-eq) is due to other forms of production.

GHG emissions in other countries due to Dutch imports (19,386 kt CO_2-eq) are 50% higher than GHG emissions due to Dutch exports (13,022 kt CO_2-eq). If we account for the total carbon footprint of Dutch consumption (domestic consumption pressures 7941 kt CO_2-eq + import pressures), we see that 71% of the GHGs emitted to satisfy Dutch consumption happen abroad. In particular, 58% of this is caused by productions related to animal farming, while the remaining 42% is connected to other agricultural and forestry products. In detail, we see that cattle are responsible for 38% of import emissions and raw milk production for 14%, which combined contribute to 51% (9928 kt CO_2-eq) of the GHGs in the agricultural sector in other countries. Other countries are chiefly considered the European Union (EU 27 minus The Netherlands) (31%), African countries (26%) and Central and South America (25%). This implies that, due to the large dependency of the Dutch agricultural consumption on resources outside of the EU, 69% of agricultural emissions may prove to be difficult to mitigate without international efforts. Furthermore, a number of countries in these regions are also identified as being most vulnerable to the effects of climate change, while also having a lower GDP, which may raise questions concerning countries' responsibility and ability to effectively mitigate emissions.

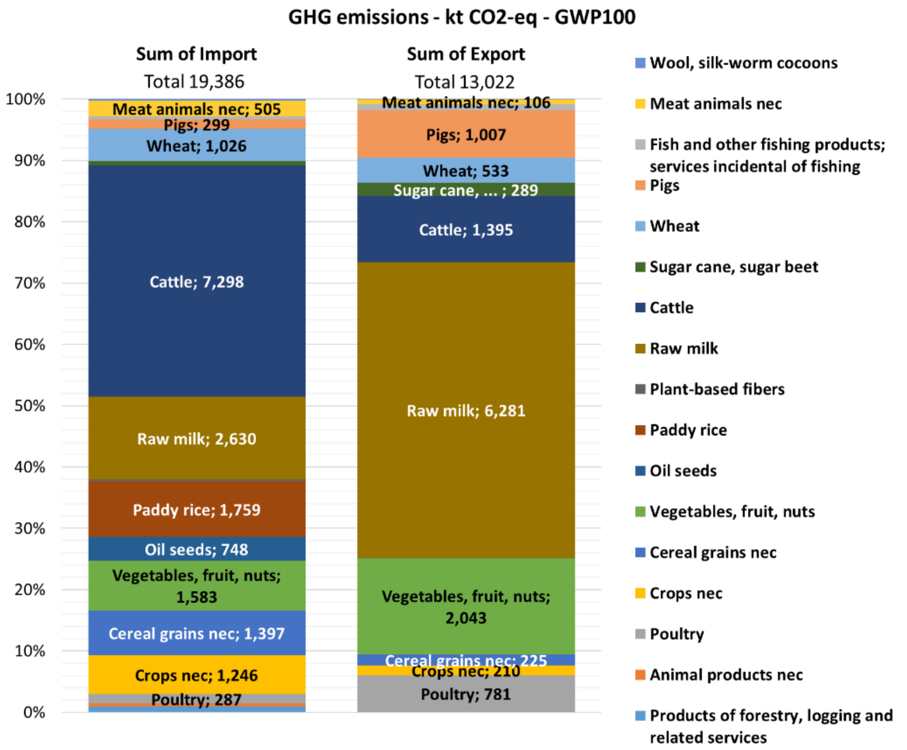

Figure 1: GHG emissions in export sectors abroad due to Dutch imports, and in export sectors of The Netherlands due to purchases abroad. Values expressed in percentage on the axis and in absolute terms inside the chart. Data: EXIOBASE V3 year 2011

Emissions per Euro Value Added

The analysis of products' GHG emissions per million EUR (M€) of value added (Figure 2) shows that nearly all Dutch production is able to emit less per unit of value added in comparison with production in other countries. This is true in all cases except for the production of vegetables, fruit, nuts and fish and other fishing products. The rest of production appears to be less emitting in The Netherlands than in the countries of import. Strictly from the perspective of containing GHG emissions at the same value added level, an argument can be built in favor of outsourcing the production of vegetables, fruit, nuts and fish and other fishing products. With the same logic, it may be worthwhile to consider which products can be produced in The Netherlands. Naturally, this strategy may not be possible for all types of sub-products but it could prove to be a worthwhile investigation. In fact, this may be of particular relevance for cattle, raw milk and cereal grains, which are more highly emitting abroad relative to value added than in The Netherlands.

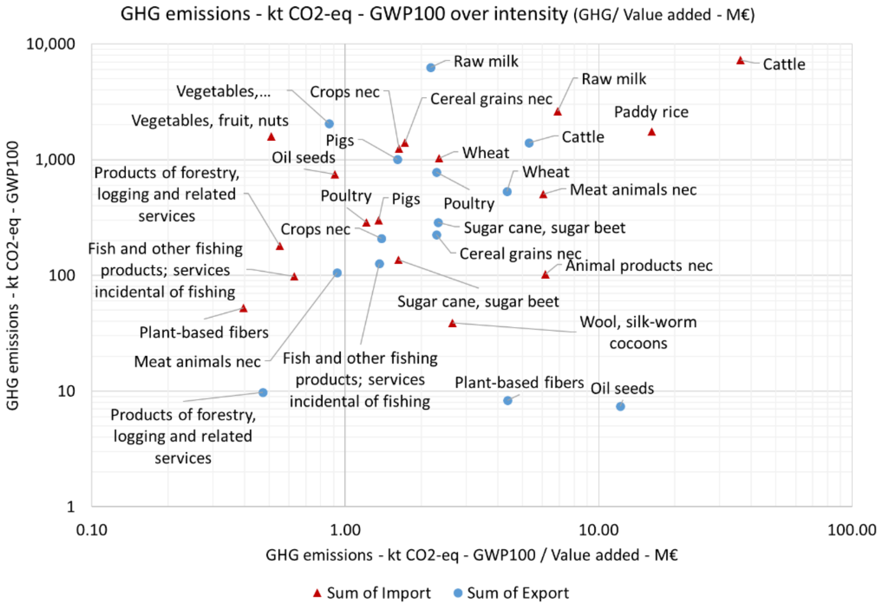

Figure 2: GHG emissions by product (y-axis) plotted against the GHG emissions intensity per million EUR of value added created by the same product (x-axis). Bottom-left corner: best; top-right corner: worst. Data: EXIOBASE V3 year 2011

These considerations are an important contribution to the current GHG emissions and, by extension, nitrogen reduction plans in The Netherlands. Specifically, since the reduction of livestock is one of the main points of the plans (Ministerie van Landbouw, 2020), care should be taken to ensure that production is not simply outsourced to countries that perform the worst according to Figure 2, as this may ultimately represent a lose–lose situation where agricultural goods are produced in countries where they emit the most and that also contribute less to the global GDP. A more detailed breakdown of the geographical performance can be found in Annex I of this study.

2.3.2 Land Use

Half of the world's habitable land is used for agriculture, resulting in disruption of ecosystems, landscape changes and loss of biodiversity (Ritchie & Roser, 2013). For instance, 86% of at-risk species are threatened by agriculture (IPBES, 2019; IUCN, 2020). As such, land use is an important metric to understand the disruption of the natural environment by the agricultural sector.

Land Use in Export and Import

The analysis presented in Figure 3 shows the impacts of the agricultural sector on land use in and outside of The Netherlands due to Dutch exports and imports. Most of the land use takes place outside of The Netherlands. In fact, Dutch exports are responsible for the use of 9282 km^2 in The Netherlands, while imports are responsible for 280,525 km^2 in other countries.

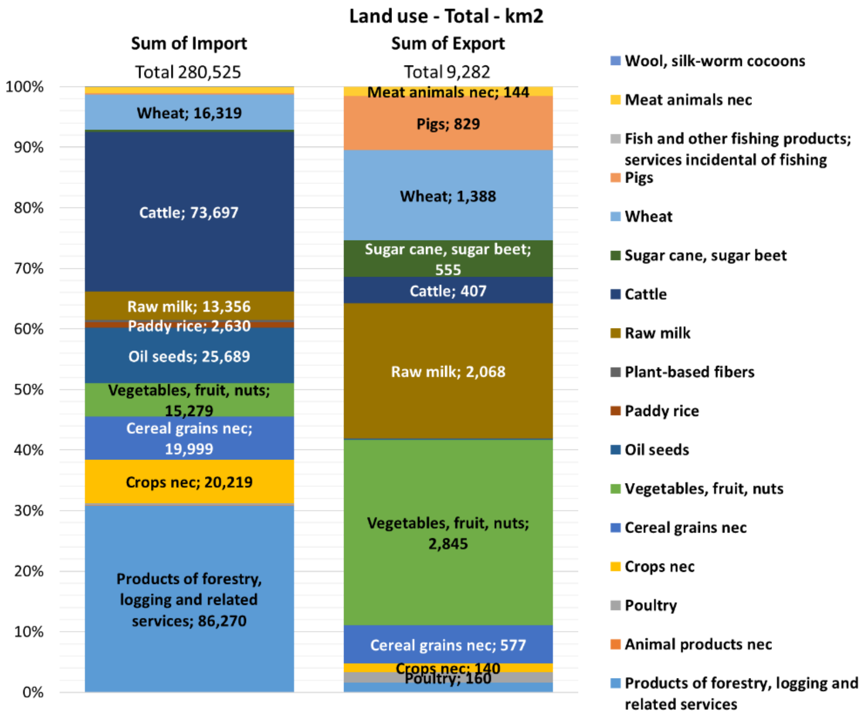

Figure 3: Land use in export sectors abroad due to Dutch imports, and in export sectors of The Netherlands due to purchases abroad. Values expressed in percentage on the axis and in absolute terms inside the chart. Data: EXIOBASE V3 year 2011.

In The Netherlands, 60% of the land use is driven by exports to other European Union member states. Animal-derived products account for 39%, while the remaining 61% is driven by non-animal farming products. The export land use is mostly driven by the production of vegetables, fruit, nuts (31%), raw milk (22%), wheat (15%) and pigs (9%). On the other hand, land use in other countries due to Dutch imports is 30 times higher than land use in The Netherlands, which shows a high dependency on foreign resources. In particular, land use due to imports takes place for 29% in Asia and the Pacific, 16% in the Middle East, 8% in the EU (minus The Netherlands), 8% in Russian Federation and 8% in Australia. Moreover, 33% (92,073 km^2) of the land use is driven by agricultural activities that do not concern animal farming directly. In fact, the most impactful products are products of forestry, logging and related services, at 31% of the total (86,270 km^2), and cattle at 26% (73,697 km^2).

Land Use in Relation to Value Added

Figure 4 shows that, in most cases, imported agricultural products are largely inefficient in the use of land in comparison with the export production of The Netherlands. It also implies that the issue related to land use (e.g., biodiversity loss) may be most severe in the countries of import. As previously shown, 92% of the land use due to imports for Dutch consumption occurs outside of the EU.

To improve the sustainability of the agricultural sector, The Netherlands may have to employ different strategies to ensure that production uses land efficiently also abroad. Some of these strategies could be importing products from countries where land use is most efficient, redirecting some of the exports toward domestic consumption or investing in capacity building and sustainable agricultural practices in importing countries. These are important considerations to keep in mind also from an EU policy perspective (i.e., EU common agricultural policy, From Farm to Fork and biodiversity policies).

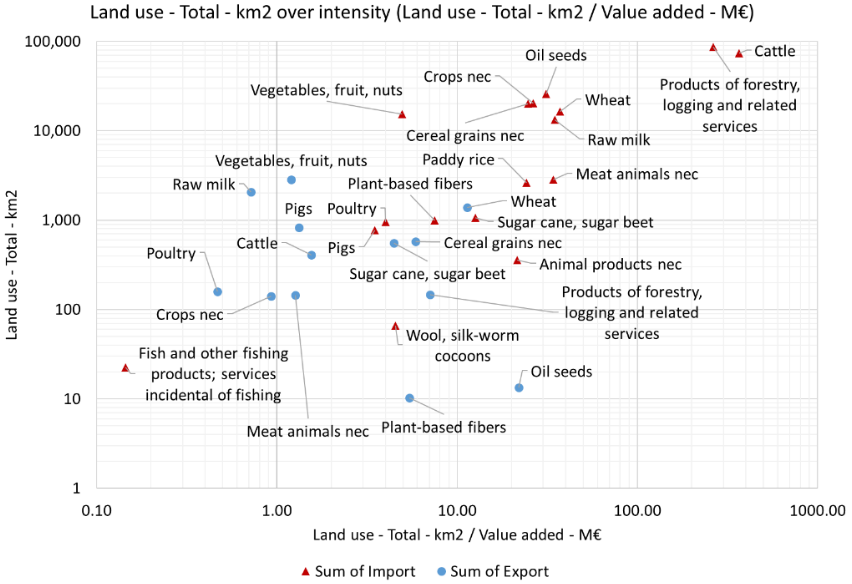

Figure 4:Land use by product (y-axis) plotted against the land use intensity per million EUR of value added created by the same product (x-axis). Bottom-left corner: best; top-right corner: worst. Data: EXIOBASE V3 year 2011

2.3.3 Water Consumption

Water is a crucial resource in our current world of increasing population and affluence. It is a resource that hosts 10% of all known species (Strayer & Dudgeon, 2010) and on which agriculture relies heavily. In fact, water withdrawal by agriculture amounts to 69% of all water withdrawn globally and 21% in Europe (FAO, 2022). For this reason, it is important to understand where and how water is being consumed due to agriculture by the Dutch economy. In this analysis, we focus on water consumption (i.e., fresh water permanently used by the product).

Water Consumption in Export and Import

Figure 5 shows that water consumption due to Dutch exports is mainly driven by the production of crops not elsewhere classified, at 59% (1977 M.m^3), which include wheat at 17% (583 M.m^3) and vegetables, fruit and nuts at 9% (305 M.m^3). Products exported related to animal farming appear to have a small direct contribution to water consumption in The Netherlands, accounting for 4.7% of the total. Exports toward other EU member states appear to take the largest share (47%), and the rest is distributed across all the other countries and regions in minor shares.

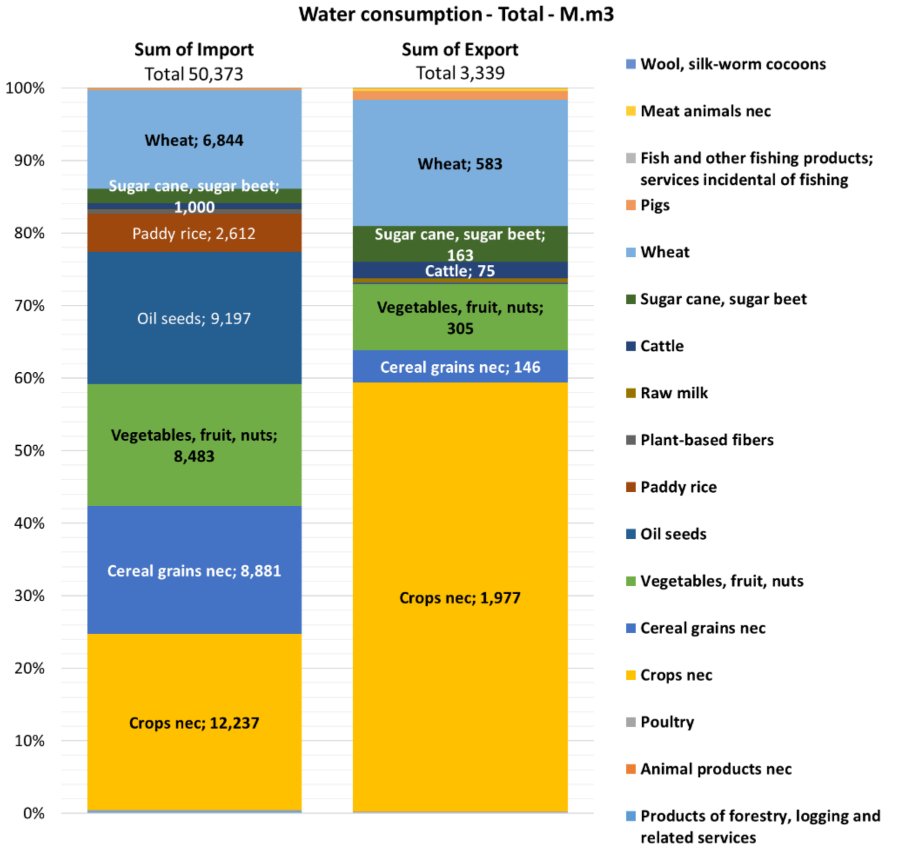

Figure 5: Water consumption in export sectors abroad due to Dutch imports, and in export sectors of The Netherlands due to purchases abroad. Values expressed in percentage on the axis and in absolute terms inside the chart. Data: EXIOBASE V3 year 2011.

Imported agricultural products have a much higher impact than exported products. Agricultural water consumption by import amounts to 50,373 M.m^3, which is 15 times greater than water consumption due to exports. In particular, 19% of the water consumption takes place in Asia, 6% in European countries outside of the EU (Non-EU + Russian Federation) and 3% in other EU member states.

The largest direct contributors are crops not elsewhere classified, at 24% (12,237 M.m3), cereal grains not elsewhere classified, at 18% (8881 M.m^3), oil seeds at 18% (9197 M.m3), vegetables, fruit and nuts at 17% (8483 M.m^3) and wheat at 14% (6844 M.m^3). Moreover, in this case, the direct water consumption of animal farming is marginal (1%) in comparison

with the demand of other agricultural products. However, it is important to keep in mind that our analysis only considers the direct impacts of production and that one third of global cropland is used for livestock feed production (Bringezu et al., 2014). For this reason, the water consumption of products related to livestock will be higher if we consider the total product water footprint.

Water Consumption in Relation to Value Added

The analysis of the intensity of water consumption over value added (Figure 6) shows the vast majority of products are related to animal farming as the best performer for both import and export products. The only exception is for imported cattle, which has the highest direct water consumption of all animal-based products and the worst intensity. Furthermore, generally, animal-based products for export consume less water per million EUR of value added than their imported counterparts. However, much of the production of crops is in fact destined as fodder for animal farming. Imported products of the grass family, as well as vegetables, fruit and nuts, appear to consume the greatest amount of water both in absolute terms and intensity.

Whether it is animal-based products or not, there is a clear division between imported and exported products, where the former appears to perform systematically worse than the latter. However, this is chiefly due to the fact that environmental pressures due to Dutch consumption occur in the largest part abroad, while, at the same time, The Netherlands is often one of the nodes of complex supply chains. Therefore, the graph does not indicate a higher environmental efficiency of agricultural products (to which other countries may aspire) but it is instead an indication that if The Netherlands is to implement sustainable water consumption practices, it needs to address its environmental pressures abroad.

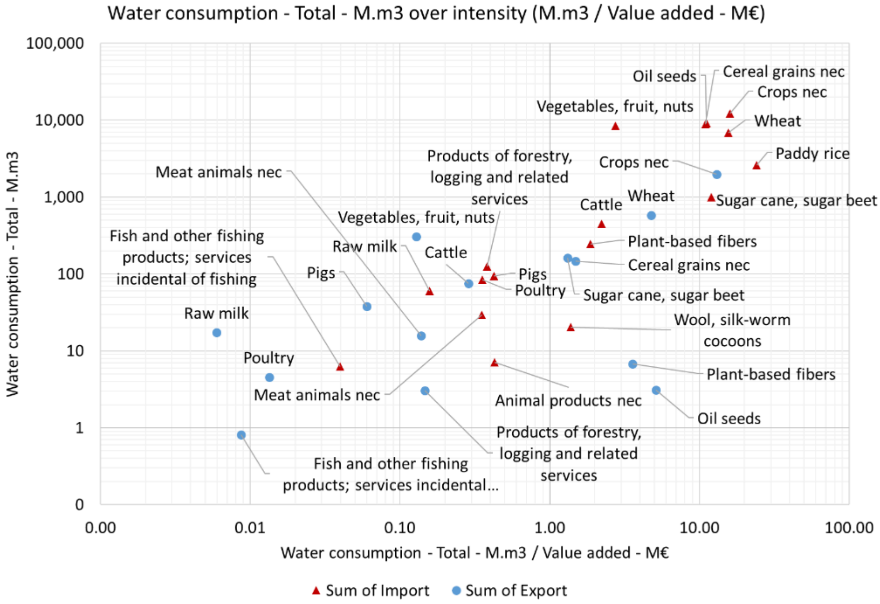

Figure 6: Water consumption by product (y-axis) plotted against the land use intensity per million EUR of value added created by the same product (x-axis). Bottom-left corner: best; top-right corner: worst. Data: EXIOBASE V3 year 2011.

2.4 Discussion

It is important to note that in the presented results, the imbalance between impacts abroad and those in The Netherlands is probably greater than represented as our chosen approach only captures direct pressures. This is very likely the case for animal products as, typically, the production of animal feed has high land use, which would not be accounted for in the direct land use of animal farming. This means that the results need to be read with care as they may lead to an underestimation of environmental pressures across the full life cycle.

In addition, it is important to recognize that uncertainties in this type of data and analysis are inevitable. This article is based on EXIOBASE (Stadler, Wood, Bulavskaya, Södersten, Simas, Schmidt, Usubiaga, Acosta-Fernández, Kuenen, Bruckner, Giljum, Lutter, Merciai, Schmidt, Theurl, Plutzar, Kastner, Eisenmenger, Erb, Koning, et al., 2018; Wood et al., 2015). To create this database, dozens of national input–output tables are combined—and also adjusted, since the total im- ports in these IO tables often mismatch the total exports per product group on a global scale. As a result, differences may exist between the national official statistics and EXIOBASE (Walker et al., 2017). Furthermore, while EXIOBASE is one of the most detailed global MRIOs available, it contains only 15 agricultural product groups. As already noted in the Introduction, this may imply that imports and exports that, in this paper, have the same product category name in fact may consist of different products. Only higher detail in MRIOs can solve such issues.

2.5 CONCLUSIONS

The Dutch import of agricultural goods causes relatively high greenhouse gas emissions, and creates significant impacts related to water and land use abroad. In other words, The Netherlands drives significant environmental pressure via imports within other countries, because of Dutch consumption and production of agricultural goods. In part, it is understandable that The Netherlands creates such high pressures abroad. A densely populated country such as The Netherlands will always specialize in sectors that have a lot of value added per unit of land, while, for sparsely populated countries (from which The Netherlands partly imports), the opposite applies. However, the result is also that The Netherlands' agricultural consumption largely depends on biotic resources from abroad related to land use, water consumption and GHG emissions. This means that reducing the environmental pressures from Dutch agriculture has a clear international dimension and requires international cooperation. In this, it should be considered that countries in Africa and South America—that contribute highly to Dutch agricultural imports—have a lower national income than The Netherlands. This raises the question of whether a rich country such as The Netherlands should not take relatively more responsibility to reduce impacts outside its borders (for a more elaborate discussion on responsibility allocations see e.g., Kander et al., 2015; Steininger et al., 2016; Tukker et al., 2020).

To reduce the environmental impact of the Dutch agricultural sector abroad, various strategies can be considered. One of the options is to improve production efficiency in other countries. With regard to land use, further work could be done considering how agriculture and forestry can take place without major loss of biodiversity, something already stimulated by various certification organizations for wood products. It may also be considered to import from countries where biodiversity problems due to land use are limited or where production is already efficient (de Boer et al., 2019).

Another way to reduce global environmental pressures could be to replace the imports by domestic production. For many sectors and products, Dutch production seems to have a higher value added to pressure ratio as abroad. However, such a strategy is probably not really possible. First, there are restrictions in The Netherlands with regard to the use of natural resources (particularly of land). Second, as noted above, it is likely that various groups of agricultural products in EXIOBASE will not be sufficiently homogeneous. The imports of The Netherlands, in this case, concern other products besides those covered by the exports of The Netherlands.

Given the more efficient production in other countries in terms of greenhouse gas emissions per EUR of value added, it may be considered that The Netherlands would reduce its own production of vegetables, fruit, nuts and fish and other fishery products. Finally, an important point is the large number of livestock in The Netherlands, which drives the enormous import of products for animal feed, and therefore indirectly requires a lot of land and water use. A restructuring in which, in total, a similar value added is created through livestock that is smaller in size—for example, through a higher selling price for organic meat—can offer a solution for both domestic and import-induced foreign environmental pressure. Such a restructuring will also help in solving the Dutch nitrogen crisis. However, in this, care must be taken to ensure that the kind of production now taking place in The Netherlands is not simply moved abroad. After all, our analysis shows that, often, environmental pressures per unit of value added is higher abroad, which, in this case, would lead to higher overall pressures at a global level.

SUPPLEMENTARY INFORMATION

Annex I and II: https://doi.org/10.5281/zenodo.6555056

REFERENCES

Behrens, P., Rodrigues, J. F. D., Brás, T., & Silva, C. (2016). Environmental, economic, and social impacts of feed-in tariffs: A Portuguese perspective 2000-2010. *Applied Energy, 173,* 309–319. https://doi.org/10.1016/j.apenergy.2016.04.044

Bringezu, S., Schütz, H., Pengue, W., Brien, M. O., Garcia, F., Sims, R., Howarth, R. W., Swilling, M., Herrick, J., Herrero, C., Enrique, T., Sicard, L., Lambin, E., Lavelle, P., Morello, J., Nwajiuba, C., Stengel, O., Viglizzo, E., Berg, V. D., Weiss, J. (2014). *Assessing Global Land Use: Balancing consumption with sustainable supply.* In A Report of the Working Group on Land and Soils of the International Resource Panel.

de Boer, B. F., Rodrigues, J. F. D., & Tukker, A. (2019). Modeling reductions in the environmental footprints embodied in European Union's imports through source shifting. *Ecological Economics, 164*, 106300. https://doi.org/10.1016/j.ecolecon.2019.04.012

de Vries, J. L., & te Riele, H. R. M. (2006). Playing with Hyenas:Renovating Environmental Product Policy Strategy. *Journal of Industrial Ecology, 10*(3), 111–127. https://doi.org/10.1162/jiec.2006.10.3.111

Eker, S., Reese, G., & Obersteiner, M. (2019). Modelling the drivers of a widespread shift to sustainable diets. *Nature Sustainability, 2*(8), 725–735. https://doi.org/10.1038/s41893-019-0331-1

EUROSTAT. (2008). *Eurostat Manual of Supply, Use and Input-Output Tables. In Methodologies and working papers*, Economy and finance. http://ec.europa.eu/eurostat

FAO. (2022, July 4). *AQUASTAT - FAO's Global Information System on Water and Agriculture.* Https://Www.Fao.Org/Aquastat/En/Databases/. https://www.fao.org/aquastat/en/databases/

Hoekstra, R., & van den Bergh, J. C. J. M. (2006). Constructing physical input–output tables for environmental modeling and accounting: Framework and illustrations. *Ecological Economics, 59*(3), 375–393. https://doi.org/10.1016/j.ecolecon.2005.11.005

IPBES. (2019). *Global Assessment Report on Biodiversity and Ecosystem Service.* Debating Nature's Value. https://doi.org/10.1007/978-3-319-99244-0_2

IUCN. (2020). *The IUCN Red List of Threatened Species.* https://www.iucnredlist.org/en

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., & Hertwich, E. G. (2016). Environmental Impact Assessment of Household Consumption. *Journal of Industrial Ecology, 20*(3), 526–536. https://doi.org/10.1111/jiec.12371

Kander, A., Jiborn, M., Moran, D. D., & Wiedmann, T. O. (2015). National greenhouse-gas accounting for effective climate policy on international trade. *Nature Climate Change, 5*(5), 431–435. https://doi.org/10.1038/nclimate2555

Kron, W., Löw, P., & Kundzewicz, Z. W. (2019). Changes in risk of extreme weather events in Europe. *Environmental Science and Policy.* https://doi.org/10.1016/j.envsci.2019.06.007

Leontief, W. (1970). Environmental Repercussions and the Economic Structure: An Input-Output Approach. *The Review of Economics and Statistics, 52*(3), 262–271. https://doi.org/10.2307/1926294

Ligtvoet, W. (2015). *Adaptation to climate change in The Netherlands – Studying related risks and opportunities. In PBL Netherlands Environmental Assessment Agency.* PBL Netherlands Environmental Assessment Agency. www.pbl.nl/en

Marques, A., Martins, I. S., Kastner, T., Plutzar, C., Theurl, M. C., Eisenmenger, N., Huijbregts, M. A. J., Wood, R., Stadler, K., Bruckner, M., Canelas, J., Hilbers, J. P., Tukker, A., Erb, K., & Pereira, H. M. (2019). Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nature Ecology & Evolution, 3*(4), 628–637. https://doi.org/10.1038/s41559-019-0824-3

Miller, R. E., & Blair, P. D. (2009). *Input—Output Analysis: Foundations and Extensions.* Cambridge University Press, 784. https://doi.org/10.1017/CBO9780511626982

Ministerie van Landbouw, N. en V. (2020, February 7). Kamerbrief maatregelen landbouw en verdere impuls gebiedsgerichte aanpak—Kamerstuk—Aanpak Stikstof [Kamerstuk]. *Ministerie van Landbouw, Natuur en Voedselkwaliteit.* https://www.aanpakstikstof.nl/documenten/kamerstukken/2020/02/07/kamerbrief-7-februari-2020

Moran, D. D., Wackernagel, M. C., Kitzes, J. A., Heumann, B. W., Phan, D., & Goldfinger, S. H. (2009). Trading spaces: Calculating embodied Ecological Footprints in international trade using a Product Land Use Matrix (PLUM). *Ecological Economics, 68*(7), 1938–1951. https://doi.org/10.1016/j.ecolecon.2008.11.011

Nijdam, D. S., Wilting, H. C., Goedkoop, M. J., & Madsen, J. (2005). Environmental Load from Dutch Private Consumption: How Much Damage Takes Place Abroad? *Journal of Industrial Ecology, 9*(1–2), 147–168. https://doi.org/10.1162/1088198054084725

Ritchie, H., & Roser, M. (2013). *Land Use. Our World in Data.* https://ourworldindata.org/land-use

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J. H., Theurl, M. C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., … Tukker, A. (2018). EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *Journal of Industrial Ecology, 22*(3), 502–515. https://doi.org/10.1111/jiec.12715

Steininger, K. W., Lininger, C., Meyer, L. H., Muñoz, P., & Schinko, T. (2016). Multiple carbon accounting to support just and effective climate policies. *Nature Climate Change, 6*(1), Article 1. https://doi.org/10.1038/nclimate2867

Strayer, D. L., & Dudgeon, D. (2010). Freshwater biodiversity conservation: Recent progress and future challenges. *Journal of the North American Benthological Society.* https://doi.org/10.1899/08-171.1

Sun, Z., Behrens, P., Tukker, A., Bruckner, M., & Scherer, L. (2022). Shared and environmentally just responsibility for global biodiversity loss. *Ecological Economics, 194,* 107339. https://doi.org/10.1016/j.ecolecon.2022.107339

Tukker, A., & Dietzenbacher, E. (2013). GLOBAL MULTIREGIONAL INPUT–OUTPUT FRAMEWORKS: AN INTRODUCTION AND OUTLOOK. *Economic Systems Research, 25*(1), 1–19. https://doi.org/10.1080/09535314.2012.761179

Tukker, A., Goldbohm, R. A., de Koning, A., Verheijden, M., Kleijn, R., Wolf, O., Pérez-Domínguez, I., & Rueda-Cantuche, J. M. (2011). Environmental impacts of changes to healthier diets in Europe. *Ecological Economics, 70*(10), 1776–1788. https://doi.org/10.1016/j.ecolecon.2011.05.001

Tukker, A., Pollitt, H., & Henkemans, M. (2020). Consumption-based carbon accounting: Sense and sensibility. *Climate Policy, 20*(sup1), S1–S13. https://doi.org/10.1080/14693062.2020.1728208

van Dooren, C., Marinussen, M., Blonk, H., Aiking, H., & Vellinga, P. (2014). Exploring dietary guidelines based on ecological and nutritional values: A comparison of six dietary patterns. *Food Policy, 44,* 36–46. https://doi.org/10.1016/j.foodpol.2013.11.002

Walker, A., Zult, D., Hoekstra, R., Berg, M. van der, & Dingena, G. (2017). *Footprint calculations using a Dutch national accounts consistent Exiobase.* https://www.cbs.nl/en-gb/custom/2017/36/footprint-calculations-using-snac-exiobase

Westhoek, H., Lesschen, J. P., Rood, T., Wagner, S., De Marco, A., Murphy-Bokern, D., Leip, A., van Grinsven, H., Sutton, M. A., & Oenema, O. (2014). Food choices, health and environment: Effects of cutting Europe’s meat and dairy intake. *Global Environmental Change, 26,* 196–205. https://doi.org/10.1016/j.gloenvcha.2014.02.004

Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., de Koning, A., Kuenen, J., Schütz, H., Acosta-Fernández, J., Usubiaga, A., Simas, M., Ivanova, O., Weinzettel, J., Schmidt, J. H., Merciai, S., & Tukker, A. (2015). Global sustainability accounting-developing EXIOBASE for multi-regional footprint analysis. *Sustainability (Switzerland), 7*(1), 138–163. https://doi.org/10.3390/su7010138

3 MODELING THE CIRCULAR ECONOMY IN ENVIRONMENTALLY EXTENDED INPUT-OUTPUT TABLES: METHODS, SOFTWARE AND CASE STUDY

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ABSTRACT

A circular economy is an industrial system that is restorative or regenerative by intention or design. During the last decade, the circular economy became an attractive paradigm to increase global welfare while minimizing the environmental impacts of economic activities. Although several studies concerning the potential benefits and drawbacks of policies that implement the new paradigm have been performed, there is currently no standardized theoretical model or software to execute such assessment. In order to fill this gap, in the present paper we show how to perform these analyses using Environmentally Extended Input-Output Analysis. We also describe a Python package (pycirk) for modelling Circular Economy scenarios in the context of the Environmentally Extended Multi-Regional Input-Output database EXIOBASE V3.3, for the year 2011. We exemplify the methods and software through a what-if zero-cost case study on two circular economy strategies (Resource Efficiency and Product Lifetime Extension), four environmental pressures and two socio-economic factors.

KEYWORDS

Circular Economy, Interventions, EEIOA, Software, Policy, Scenarios

3.1 INTRODUCTION

The current global challenges of climate change and resource supply risk (European Commission, 2018) demand concrete strategies and actions to reach a sustainable society (UNEP, 2011). While various proposals for this future societal state exist (Geng et al., 2016; Sacchi-Homrich et al., 2018), in recent times a paradigm that has gained traction is the Circular Economy (CE): an economy that is "... restorative and regenerative by design, and aims to keep products, components, and materials at their highest utility and value at all times." (EMF, 2012). Decision makers supporting these objectives can employ different strategies intervening at multiple levels (Ghisellini et al., 2016): a) macro-level, by changing regional fiscal and economic conditions; b) meso-level, by changing the way supply-chains are organized; c) micro-level, by changing the way we produce and use materials and products. In this process, decision makers are faced with unknowns over potential benefits and undesired effects of their decisions (Faucheux and Froger, 1995). This is due to the complexity and interconnectedness of economy and environment (Knights et al., 2014). In order to shine light on these complex systems, economic-environmental models can be used (Fauré et al., 2017). Computable General Equilibrium (CGE) and Input-Output (IO) models are the most widely employed ones for the assessment of CE (Kronen et al., 2010). The two models have distinct characteristics that make them suitable for different type of analyses (de Koning, 2018). CGE is a macro-economic model broadly used for its dynamic features and endogenous inclusion of price dynamics, investment and tax relations. IO, in its various forms, is a static structural model which provides a high resolution of sectors and structural economic composition. This makes IO a useful tool for the impact assessment of supply-chains (de Koning, 2018). Both models have been used to assess the potential environmental and economic impacts of CE (McCarthy et al., 2018).

Through the use of a national CGE model of 2000 for South Korea, Kang et al. (2006) estimated the effects of increasing waste recycling and pollution management policies. They showed potential losses of 0.2% in GDP as a result of reduction of environmental pressures. In a study by WRAP on CE for Britain (WRAP, 2015), the authors investigated multiple interventions, such as reuse, recycling, servitization, and repairing and remanufacturing.

Their findings showed a reduction of unemployment rate of 0.1-0.2 percentile points by 2030. Wijkman and Skanberg (2015) analyzed CE effects on CO2 emissions, employment and trade balance. Using 2009 WIOD data (Timmer et al., 2015) for 5 EU countries (Finland, France, the Netherlands, Spain and Sweden), they simulated measures for renewable energy transition, and energy and resource efficiency. Their results showed a reduction of 70% CO2, 875000 created jobs, and an improvement of 2% of the trade balance.

Rutherford et al. (EMF, 2015), employed a CGE model based on GTAP-8 aggregated to 5 global macro-regions and 16 sectors. The study focused on technology shifts in private transport, housing and food production. Results showed that CE could deliver 48% CO2 emissions reductions by 2030 and 83% by 2050 across the analyzed sectors. The study also showed that household disposable income in 2050 would be higher by 12 percentile points in comparison with current linear economy projections.

(Tisserant et al., 2017) analyzed the waste treatment and footprints in the circular economy using the IO database EXIOBASE v2 in the Waste-IO (WIO) format. They observed that despite the difference in waste generation among countries, there is a significant potential for closing material cycles in all regions regardless of the level of country's income.

(Winning et al., 2017) developed a multi-regional macro-econometric model (ENGAGE-materials) using EXIOBASE v2 and GTAP-9. Through the model they showed a reduction of 0.02% in total CO2 and an increase of 0.03% in GDP due to the doubling of yearly scrap availability between 2017 and 2030.

More recently, (Wiebe et al., 2019) presented a global CE scenario to 2030 using EEIOA in EXIOBASE. Their study investigated the impact of recycling, higher material efficiency and repair, reuse and recycling. Results show that reduction in raw material extraction used of 10% with a positive but small impact on employment around 2%.

As shown by these studies, there is still limited information on impacts and indirect effects of the application of the circular economy (Rizos et al., 2017). In particular, more technology-based assessments are needed (McCarthy et al., 2018). IO is a suitable model for the creation of this type of "what-if" scenarios through the application of exogenous changes (de Koning, 2018).

One of the advantage of this type of approach is the level of transparency in assumptions (de Koning, 2018). This is especially important for CE impact assessment as the variety of approaches makes it difficult to compare studies (Rizos et al., 2017). Previous studies have tried to categorize types of interventions within CE (EMF, 2012; Aguilar-Hernandez et al., 2018), their fundamental waste management models (Yifang, 2007; Li, 2012) and indicators (Iacovidou et al., 2017). However, there is still a need for current CE assessment methods to become more comparable and robust in order to serve as policy tools (Rizos et al., 2017).

In order to gain insights for policies, IO databases and methods can be used in specialized software. An overview of such tools is available in Annex II. From this analysis, it appeared that no viable free and open-source alternative is available for the construction and the analysis of complex scenarios using detailed IO databases like EXIOBASE (Tukker et al., 2013; Stadler et al., 2018).

Hereby we present a software and systematic methods to build complex CE counterfactual (what-if) scenarios with Environmentally Extended IO (EEIO) tables. We focus on the creation of CE scenarios for two CE strategies: Product Lifetime Extension (PLE) and Resource Efficiency (RE) (Aguilar-Hernandez et al., 2018). Furthermore, instead of the hybrid unit data (Merciai & Schmidt, 2018) in the WIO framework (Nakamura & Kondo, 2009) as suggested by (Aguilar-Hernandez et al., 2018b) we employ the monetary EEIO framework, as the base for the implementation of the strategies. This is because the hybrid data does not contain value added and employment inputs (Merciai & Schmidt, 2018), key indicators used in previous literature about the implementation of CE strategies.

We first present a CE scenario implementation framework for EEIO tables. Secondly, the data and Python package developed for this study are described. At last, we exemplify methods and software in a case study concerning 2 CE strategies: Product Lifetime Extensions (PLE) and Resource Efficiency (RE). The results section presents the findings and is followed by discussions and conclusions. Furthermore, scenario assumptions and modelling choices and complete results are shown in Annex I.

3.2 METHODS

3.2.1 CE policy modelling framework

CE policies are often articulated at different levels of detail, so it is convenient to define a clear modelling framework (Illustrated in figure 1). We begin by asserting that the objective of a CE policy is always the implementation of the circular economy paradigm. In order to achieve this objective different strategies exist. There are various categorizations of CE strategies such as ReSOLVE (EMF, 2015c), (Kirchherr et al., 2017a), and (Bocken et al., 2016). However, in this study we follow the 4-strategy classification of Aguilar-Hernandez et al. (2018) which consists of: Product Lifetime Extension (PLE); Resource Efficiency (RE); Closing Supply Chains (CSC); Residual Waste Management (RWM).

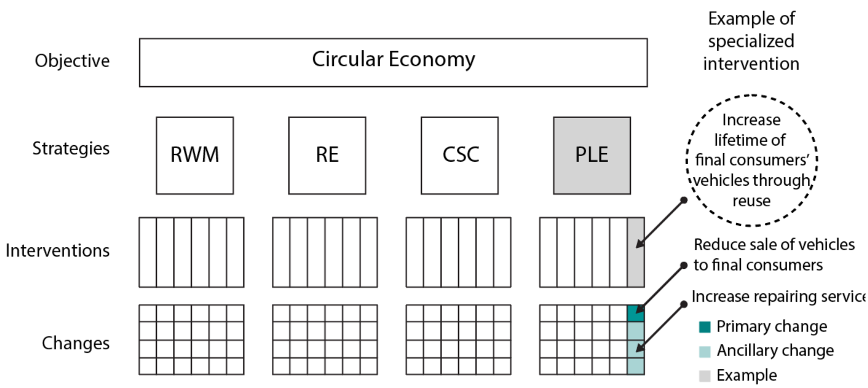


Figure 1: CE policy modelling framework – RWM = Residual Waste Management; RE = Resource Efficiency; CSC: Closing Supply Chains; PLE: Product Lifetime Extensions

In the analyzed literature, the terms strategies and interventions are often used interchangeably. However, we believe that a distinction between these two concepts is needed. We define strategies as sets of policy interventions and improvement options (or simply interventions). For example, PLE can be achieved, among others, by reuse and remanufacturing, or delaying products' replacement (Allwood and Cullen, 2015). In other words, while these two interventions aim at the same objective, the extension of product's life, the way they are implemented is different. We further distinguish between a general description of interventions and specialized interventions. An intervention (e.g. reuse and remanufacturing) is specialized when it refers to a specific product or application (e.g. increase lifetime through reuse and remanufacturing in final consumers' vehicles). Interventions are modelled through sets of changes that affect the production and consumption systems. We further distinguish between primary and ancillary changes. For instance, if the intervention concerns increasing the lifetime of vehicles the primary change would be a reduction of sale of vehicles resulting from less consumers needing to replace their vehicles. A corresponding ancillary change would be the potential increase in repairing services caused by a higher utilization of the good. We show this conceptual approach in Figure 1.

3.2.2 Environmentally Extended Input-Output (EEIO) analysis

Environmentally Extended Input-Output (EEIO) analysis (Leontief, 1970; Suh, 2009) is based on Input-Output (IO) analysis (Leontief, 1951; Miller and Blair, 2009) and deals with the quantification of environmental pressures that take place along the supply chain of goods and services, by assuming that production structure remains fixed. The basic Leontief demand-driven model can be framed such that a stimulus vector of final demand leads to a set of emissions occurring in each production sector as:

$$\mathbf{r} = \mathrm{diag}(\mathbf{b})(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} \tag{1}$$

In the preceding expression $\mathbf{r}$ is the column vector of emissions occurring in each production sector (the response variable) and $\mathbf{y}$ is the column vector of final demand of products delivered by each sector (the control variable). The parameters of the model are the column vector $\mathbf{b}$ of environmental intensities (environmental pressure per unit of economic output) and $\mathbf{A}$ is a matrix of technical coefficients (whose entry ij is the volume of inputs from sector i that are required to generate one unit of output of sector j). diag stands for diagonal matrix and $\mathbf{I}$ is the identity matrix.

The technical coefficient matrix is calculated as $\mathbf{A} = \mathbf{Z}\,\mathrm{diag}(\mathbf{x})^{-1}$, where $\mathbf{Z}$ is the matrix of inter-industry transactions and $\mathbf{x}$ is the column vector of total output of each sector, $\mathbf{x} = \mathbf{Z}\,\mathbf{i} + \mathbf{Y}\,\mathbf{i}$, the row sum of $\mathbf{Z}$ and $\mathbf{Y}$, where the latter is a matrix whose columns represent the final demand of different consumption categories (e.g., households, government, investment), and $\mathbf{i}$

is a vector column of ones. For the purpose of this study the stimulus vector entering Eq. 1 is assumed to be row sum of the final demand matrix, $\mathbf{y} = \mathbf{Y}\,\mathbf{i}$. For some environmental pressures (e.g., global warming) there are direct emissions resulting from final consumption activities (e.g., the combustion of fossil fuels by households leads to the emission of greenhouse gases). When that is the case it is necessary to include emissions from final demand to obtain total emissions, r_{tot}, as:

$$r_{tot} = \mathbf{r}'\,\mathbf{i} + b_y\,y \qquad (2)$$

In the previous expression prime (') denotes transpose, b_y is a scalar representing the intensity of final demand environmental pressure (i.e., emissions caused by households per unit of final demand), and y is a scalar of total final demand obtained as $\mathrm{y} = \mathbf{y}'\,\mathbf{i}$, i.e., the column sum of the final demand stimulus vector. If more information is available, the intensity of final consumption environmental pressures can in principle be disaggregated by product category.

Note that in the application the system used is multiregional. That is, each entry of $\mathbf{b}$, $\mathbf{A}$ or $\mathbf{Y}$ identify not only a row and/or column economic sector or final demand category but also a region (e.g., EU or Rest of the World).

3.2.3 Baseline and counterfactual scenario

In order to assess the environmental or socio-economic impact of implementing a CE policy we compare the impact that occurs in the baseline and the impact that occurs in a counterfactual scenario in which the changes corresponding to the CE intervention and strategy have been implemented. More formally, the impact of the CE policy is $\Delta\mathbf{r} = \mathbf{r}^* - \mathbf{r}$, where $\mathbf{r}$ is the impact in the baseline scenario, defined in Section 2.1, and $\mathbf{r}^*$ is the impact in the counterfactual scenario, defined as:

$$\mathbf{r}^* = \mathrm{diag}(\mathbf{b}^*)(\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{Y}^*\,\mathbf{i} \qquad (3)$$

If there are final consumption emissions, we can further define $\Delta r_{tot} = r^*_{tot} - \mathrm{r}_{tot}$ where

$$r^*_{tot} = (\mathbf{r}^*)'\,\mathbf{i} + b^*_y\,y^* \qquad (4)$$

A counterfactual scenario (an object adjoined with *) is constructed by adjusting particular elements in the objects that define the baseline EEIO system, $\mathbf{b}$, $\mathbf{A}$, $\mathbf{Y}$ (and possibly b_y and y) with this adjustment being as faithful as possible to the concepts underlying the policy intervention, subject to the limitations of the data and model.

The counterfactual scenario is constructed by adjusting only a (possibly) small set of values of some of the matrix objects than define the EEIO system. All other entries remain identical in both scenarios. With the current methods, we do not perform any automatic rebalancing of the counterfactual scenario, as such the system may become unbalanced when changes are applied to the technical coefficient matrix $\mathbf{A}$ (i.e., total outputs differ from total inputs).

3.2.4 Change coefficients and substitution

The edit of a particular entry ij of an arbitrary $\mathbf{M}$ matrix object from the baseline to the counterfactual scenario, is performed by the software as:

$$M_{ij}^{*} = M_{ij}\,(1 - k_a) \tag{5}$$

The change coefficient (k_a) expresses the magnitude by which a value in the IO system is modified. It is obtained as the product of a technical change coefficient (k_t) which describes the intervention's maximum potential effect, and of a market penetration coefficient (k_p) describing the size of the given market affected (Wood et al., 2017), $k_a = k_t\, k_p$.

Furthermore, there might exist a substitution relation between edits in different entries. For example, a reduction in the volume of a particular material (e.g., steel) used in a production process might be compensated by an increase of another (e.g., aluminum). This type of relation is modelled as:

$$M_{ij}^{*} = M_{ij} + \alpha(M_{mn}^{*} - M_{mn}) \tag{6}$$

Here mn are the coordinates of the original change (e.g., reduction in steel) and ij are the coordinates of the substitution (e.g., increase in aluminum). α is a substitution weighting factor accounting for differences in price and physical material properties between products, materials or services.

3.2.5 Modeling CE interventions in EEIO

In this section, we show the suggested assumptions behind modelling CE interventions. These assumptions may vary depending on the specific case, so we encourage a critical reading and application. Firstly, we explain the elements that compose the modelling blueprints. We then present blueprints for modelling CE interventions under PLE and RE. Blueprints are graphic visualizations that indicate where and how changes are applied in the EEIO system in order to simulate CE interventions. They are designed with the conceptual aid of the work of Allwood and Cullen (2012) and the Ellen MacArthur Foundation (EMF, 2015c), which indicate respectively the requirements for the implementation of PLE and RE measures, and business models in the circular economy. The blueprints provide a simplified visual representation of the IO system. This simplification does not include trade. Unless otherwise specified in the assumptions, production of export/import would be subject to the same changes.

The blueprints are composed by the technical coefficient matrix ($\mathbf{A}$), final demand (y), and the environmental extensions $\mathbf{b}$ and b_y respectively. In order to facilitate the identification of points across these tables, we subdivide production and consumption activities into groups of similar economic and technical properties. These are the coordinate groups needed for the blueprints elaborated in this study:

- *Final products (fp):* fully manufactured consumer or capital goods that are not typically a component (e.g. vehicle, building, instrumentation and desktop computers);
- *Components (c):* a manufactured or semi-manufactured product that may be used as an element in production or as subcomponent of final products (e.g. engine, window, spring and metal plates);
- *Primary raw materials (pm):* virgin material resulting from extraction or the refinement of extracted materials (e.g. primary steel);
- *Secondary raw materials (sm):* recycled materials obtained from pre- and post-consumer phase (e.g. Recycled Steel);
- *Services (sr):* activities aiding the supply and maintenance of goods and value (e.g. sharing, renting, selling and repairing).

The blueprints show different symbols which indicate reductive (-), increasing (+) or undefined and case specific (◊) effects of intervention's changes. In those cases where a substitution between two commodities may apply (equation 9) the blueprint shows a star symbol (*). Following the framework presented in section 2.1, we make a distinction between primary and ancillary changes.

Figure 2 shows how interventions under PLE are modelled at the industry and final demand level. PLE is composed by a set of interventions aimed at prolonging the utility of final products or their components. We divide PLE in two interventions:

- Reuse and remanufacturing: modelled by reducing transactions of new products (or components) and increasing services (e.g. retail trade, maintenance and repairing services). The latter, an ancillary activity, may be applied either at the industrial level or final demand depending on whether specialized intervention assumes services to be internalized by firms or allocated to consumers.
- Delayed product replacement: modelled by reducing transactions of new products (or components) and increasing services in either final demand or for the sectors (depending on the assumptions). Changes in material demand to increase durability may also be needed.

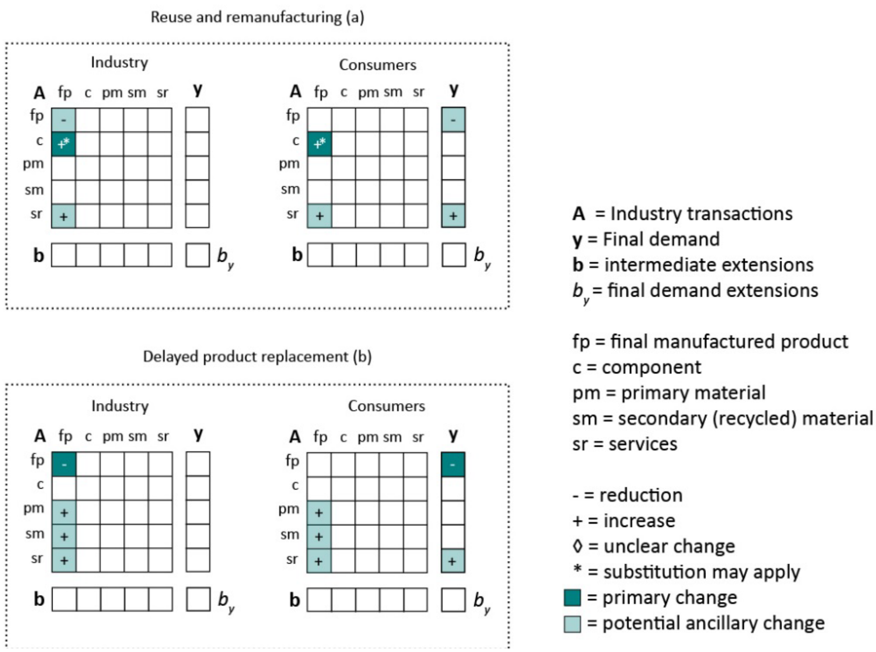
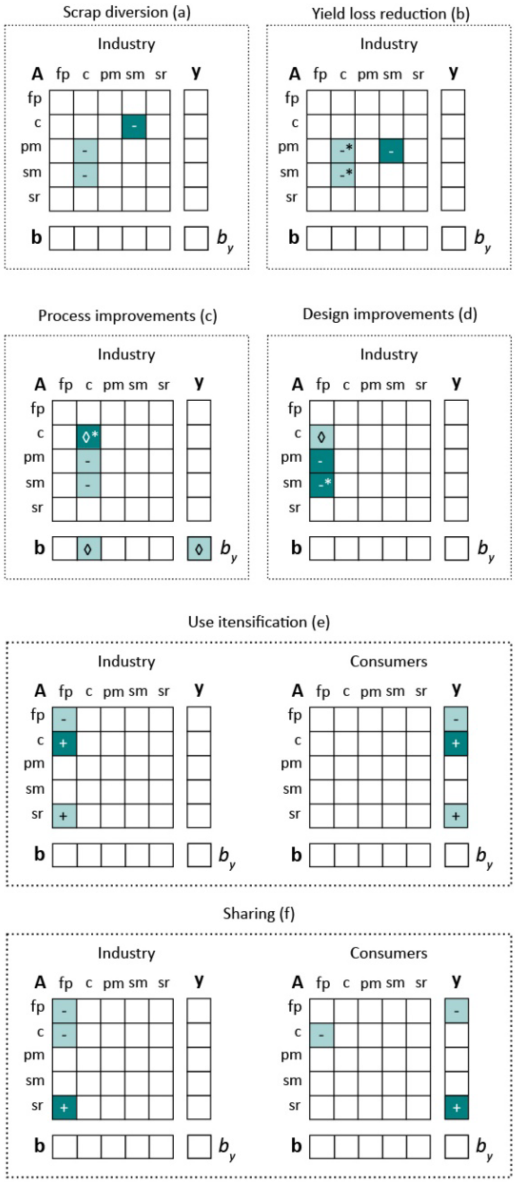


Figure 2: Product Lifetime Extension (PLE) modelling blueprints



A = Industry transactions
y = Final demand
b = intermediate extensions
b_y = final demand extensions

fp = final manufactured product
c = component
pm = primary material
sm = secondary (recycled) material
sr = services

- = reduction
+ = increase
◊ = unclear change
* = substitution may apply
= primary change
= potential ancillary change

Figure 3: Resource efficiency (RE) modelling blueprints

We define RE as a set of interventions aimed at reducing use of resources and improving performance during their use. In figure 3 we show 8 types of interventions and how they are applied:

- Scrap diversion: This simulates the reduction of swarf due to mechanical processing (e.g. during metal cutting). This is modelled by reducing the scrap going to recycling activities (secondary materials) from a specific manufacturing activity, with it we reduce also the equivalent volume of primary material used. We assume that the output of production remains unchanged. In other studies (Wiebe et al., 2019), this is performed as a market share change in the supply table of the supply-use system. However, here we apply them in the IO so that we are able to distinguish between industries generating scrap.
- Yield loss reduction: this intervention represents the reduction of physical losses at the process level; the simulation method is comparable to scrap diversion, however, it includes possible material substitutions. This is because Yield loss reduction may be obtained by both improving the environmental conditions of processes but also by substituting substances which could help deliver higher yields.
- Process improvements: replacing old technologies with more efficient ones (e.g. introduction of additive manufacturing). In the blueprints we show that the substitution of components may be required, however, it is unclear whether it would have a reductive or increasing effect. As a result of this change, materials may be substituted, however, we assume that process improvements always represent a reduction of materials used. The improvement in the process may also concern emissions intensities both at the industrial level or final consumers. For example, the improvement of the process of combustion in car engines may result in changes in the intensity of emissions during use.
- Design improvements: In this intervention we reduce the amount of materials (primary and secondary) consumed along a manufacturing activity. A change component may also be required depending on the specific case.

- Use intensification: using products or materials more over a period of time would result in higher demand for components and maintenance services while reducing the demand for new goods.
- Sharing: using products among multiple users. Here it is assumed that a firm holds the ownership of the product and allows use among multiple actors. This means that replacement of components and maintenance remains a responsibility of the firm while the sales of final products serving the same purpose are reduced.

3.3 Data, software and case study settings

3.3.1 Data

The database used is the multi-regional Supply-Use Tables (SUTs) EXIOBASE V3.3 from 2011 (Tukker et al., 2013; Wood et al., 2015; Stadler et al. 2018). We chose to employ this database for its high level of detail on product categories. Specifically, for its inclusion of primary and secondary raw materials (PRM and SRM) and environmental extensions. These characteristics make EXIOBASE a suitable option for the analysis of CE. EXIOBASE is broadly used in the analysis of policies through the use of symmetric IO tables. IO tables are calculated from SUTs through the use of various transformation methods (Eurostat, 2008). In this work we use the Product-by-Product Industry Technology Assumption (ITA). This method is commonly used by practitioners and thereby a suitable format to facilitate future comparability of studies.

3.3.2 Software

The Python Circular Economy (pycirk) software package was designed for the creation and analysis of CE scenarios, and it builds on previous software for modelling CE (Donati, 2017). This Python3 package can be used by import into a Python interpreter or a command line interface. To initialize modeling users have to specify various parameters: transformation method; directory; aggregation (bi-regional or 49 regions); make secondary (make SRM apparent during transformation from SUTs to IO, see section 3.1). The package reverts to default settings if parameters are not specified. Upon initialization a scenarios.xls file is created in the specified directory. This file works as an interface to set scenario inputs and assessment parameters through its multiple spreadsheets. The analysis sheet allows to specify assessment indicators while sheets beginning with ”scenario_” represent a scenario. These sheets are set to facilitate the integration with the methods highlighted in sections 2.3 through 2.5. Once the settings are saved, the model is run and results can be calculated for one or all scenarios. Further information on use, architecture and logic flows is available through on the software documentation (Donati, 2019b). Pycirk is made available for any practitioner interested in scenario making or further development of the tool. The software is shipped with a bi-regionally aggregated version of EXIOBASE v3.3 in pickle format. This is done to facilitate study replicability by using a common database and software. The complete multiregional database (48 regions) is also available upon request in the same format. Additional information on changes to the database can be found in Annex II.

3.3.3 Case study settings

With the case study we exemplify the use of pycirk through the analysis of global implications of applying Product lifetime extensions (PLE) and Resource efficiency (RE) CE strategies. The data used is at a bi-regional (EU-ROW) level of aggregation as our interest is in the global effects of the strategies and their significance to the EU28. For this study we also made secondary raw materials explicit in IO, an explanation of how this was done can be found in Annex II. We further elaborated the 2 CE strategies into 8 interventions (figure 2 and 3), for which we identified their specialized applications (i.e. interventions applied to a specific product). These 37 specialized interventions, their assumptions and inputs to the case study are in Annex I.a. The results from the processing of each individual intervention were used to calculate the intervention priority order for the total scenario. This processing order was based on the size of the sum of the relative change (RC) of all the indicators from the baseline. The smaller the total RC the higher the priority in the total scenario. In table 1 we show a summary of the interventions with a cumulative RC < -4%.

In the first specialized intervention “Increase average lifetime of office buildings in constructions 1.5 times”, we reduce the transactions of construction in Final demand (except households) and industry. This indicates that offices last longer and therefore there is a reduced need for building new ones. We increase by the same relative value services going to constructions to simulate more renovation and maintenance. These services are contained within the construction category.

For “Increase average lifetime of vehicles 2.3 times”, we reduce the sales of “Motor vehicles, trailers and semi-trailers” both in final demand and industry. The category "Sale, maintenance, repair of motor vehicles, motor vehicles parts, motorcycles, motor cycles parts and accessories" is increased by the same relative value in both final demand and in the technical coefficient matrix where the services intersect with motor vehicles.

In “Increase 2.5 times the intensity of use of vehicles due to higher occupancy”, we reduced transactions of cars to final demand. With it, we modelled an equivalent reduction of public transport demand. This is modelled by using the substitution formula (eq. 6) and applying a negative value to the substitution weighting factorα.

At last, “Increase average life time of electrical machineries and apparatus to final consumers 4 times”. In order to simulate a longer life in this specialized intervention, we reduced the transactions of “Electrical machineries and apparatus n.e.c.” to final demand. We increase by the same relative value the services for maintenance and repair "Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods".

Table 1: Specialized Interventions with a cumulative relative change < -4%

Strategy (Intervention)	Specialized intervention	Change type	Product category	Consumption activity	Technical Change (%)	Market pen. (%)	Substitute (SWK) (%)	Citations
Product lifetime extension **(Delayed replacement)**	Increase lifetime of office buildings in constructions 1.5 times	Primary	Construction work	Final Demand except households	-60	32.1		(Allwood and Cullen, 2012, p234; FIEC, 2019)
		Ancillary	Construction work	Construction work	60	22.7		
Product lifetime extension **(Delayed replacement)**	Increase average lifetime of vehicles 2.3 times	Primary	Motor vehicles, trailers and semi-trailers	All final demand categories	-50.7	100		(Allwood and Cullen, 2012, p234; Allwood and Cullen, 2012, p271)
		Ancillary	Sale, maintenance, repair of motor vehicles	Motor vehicles, trailers and semi-trailers	50.7	100		
Resource Efficiency **(Intensify use)**	Increase 2.5 times the intensity of use of vehicles due	Primary	Motor vehicles, trailers and semi-trailers	All final demand categories and all product categories	-60	33		(J. M. Allwood, 2015; Litman, 2019;

Strategy (Intervention)	Specialized intervention	Change type	Product category	Consumption activity	Technical Change (%)	Market pen. (%)	Substitute (SWK) (%)	Citations
	to higher occupancy	Proportional reduction to the above change	Other land transportation services	All final demand categories			-30	Mount, 2016)
		Ancillary	Sale, maintenance, repair of motor vehicles	All final demand categories and all product categories	120	33		
Product lifetime extension **(Delayed replacement)**	Increase average life time of electrical machineries and apparatus to final consumers 4 times	Primary	Electrical machinery and apparatus n.e.c.	All final demand categories	-75	100		(Allwood and Cullen, 2012, p275)
		Ancillary	Retail trade services, except of motor vehicles and motorcycles	All final demand categories	75	100		

3.4 Results

3.4.1 Impact of the strategies

Figure 4 shows the relative change (RC) of Product Lifetime Extension (PLE), Resource Efficiency (RE) and their combination (Total). Starting from the total scenario, environmental indicators are reduced by -10.1% Global Warming Potential 100-years (GWP), -12.5% Raw Material Extraction (RME), -4.3% Land Use (LU) and -14.6% Blue Water Withdrawal (BWW). BWW concerns the withdrawal of surface and ground water by the manufacturing, electricity production and domestic use sector (Eisenmenger et al., 2014). It includes all the water used which may be consumed or returned to the environment (Eisenmenger et al., 2014). LU is strongly dominated by the agricultural sector; therefore, it may see milder effects due to interventions in the product categories we analyzed.

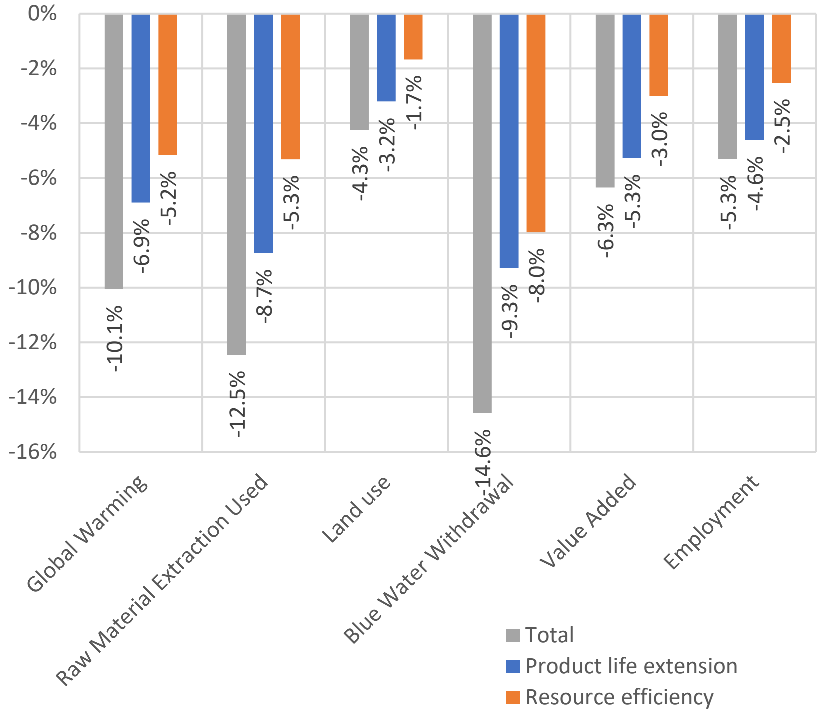
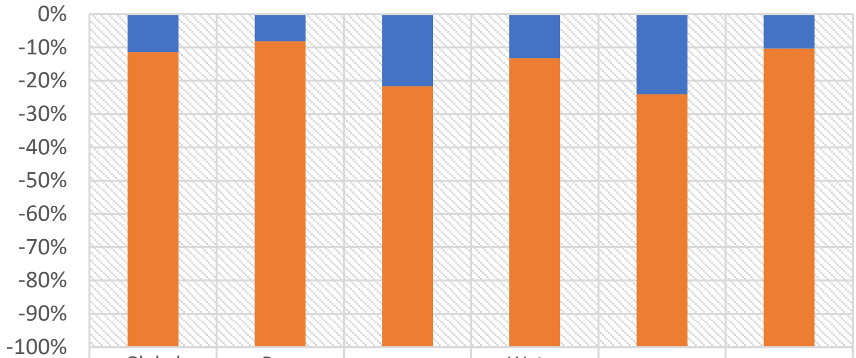


Figure 4: Global potential effects of the CE strategies and their combination

We also see a great reduction of socio-economic indicators, -6.3% Value Added (VA) and -5.3% employment. These results are in contrast with previous macro-economic studies and general aims of the CE, where economic growth is ensured while decoupling environmental impacts. This is in part logical. We focused on Life time extension. Life time extension and a more intensive use of products imply that with less product output (and hence less VA and labor) the same final demand can be satisfied. Society has no wealth loss, needs less labor and hence can provide more free time, but optically produces a lower GDP. Another explanation of this discrepancy is the absence in our model of interventions concerning investment and other dynamic changes (e.g. in price) that were included in other studies. For instance, we did not assume that as a result of a more economically efficient production, a sector may invest more in other activities nor did we include rebound effects. However, it is to be noted that the modelled interventions have a stronger relative reductive effect on almost all environmental indicators than the socio-economic indicators. That suggests that even at parity of economic performance, a circular economy could deliver environmental benefits.

Analyzing the individual strategies, PLE shows the largest contribution to reductions across all indicators: -6.9% GWP; -8.7% RME; -3.2% LU; -9.3% BWW. In terms of socio-economic indicators, PLE showed an important effect in the reductions of employment (-4.6%). RE also indicated a change of employment of -2.5% which might imply an overall difference of 2.1 points between PLE and RE. However, we obtain a -5.3% change in employment when we combine the interventions, a 0.7 point difference. This is due to the sequential processing of the interventions, producing counterfactual values in the matrix of reference at each implemented change. Furthermore, in order to understand the sensitivity of the total scenario to changes in the order of intervention, we tested different processing sequences. By modifying the order of application of the changes, we noticed that employment may vary by ~0.05 points (annex I.g). This indicates that results on employment have a mild sensitive on the way scenario inputs are processed. A similar sensitivity can also be seen in VA. On the other hand, the other impact categories remain between 0.1-0.3 percentile points.

Despite smaller effects due to RE, we still see notable improvements in environmental performance in this strategy: -5.2% GWP, -5.3% RME, -1.7% LU and -8.0% BWW. To be noticed is also the difference in GWP of the two strategies (PLE -6.9%; RE -5.2%) (Annex I.b). So PLE has deeper effects in reduction of GWP, however, a similar difference can also be observed across the other impact categories.



	Global warming GWP100 - kg CO2 eq.	Raw material extraction used - kt	Land use - km2	Water Withdrawal Blue - Total - Mm3	Value Added - M.EUR	Employment - 1000 p.
ROW	-3.850E+12	-8.984E+06	-2.578E+06	-1.151E+05	-2.517E+06	-1.462E+05
EU	-4.954E+11	-7.954E+05	-7.167E+05	-1.756E+04	-7.996E+05	-1.699E+04

Figure 5: Relative and absolute regional change of global effects due to application of CE strategies

Figure 5 shows the regional relative change due to the global application of the total scenario. As it is to be expected, the implementation of CE strategies delivers minor results on environmental reductions at the EU level in comparison with ROW (Rest Of World). In fact, if we analyze the change of environmental impacts in comparison with the regional baseline (Annex I.c), the EU showed GWP -6.4%, RME -7.8%, LU -4.1% and BWW -9.8%; while ROW showed GWP -10.9%, RME -13.1%; LU -4.3% and BWW -15.7%. At the same time, socio-economic indicators may also see a reduction in both regions. The question then remains on how the capital saved is reused by industry and final consumers in each region. Therefore, care should be given when interpreting the results as economic and environmental impacts may vary depending on how the intervention is implemented.

3.4.2 Impact of individual interventions

Finally, the interventions are analyzed (figure 6 and 7). We first analyze the interventions included in PLE, Delayed replacement and Reuse and remanufacturing. Delayed replacement shows major reductions in comparison with the other interventions (-6.06% GWP; -7.86% RME; -3.06% LU; -7.74% BWW, -4.78% VA, -4.21% E). The specialized interventions (annex I.f) mainly responsible for the strength in delayed replacement are the increase in average lifetime of office buildings and longer lifetime of vehicles. Office buildings were increased 1.5 times (J. Allwood & Cullen, 2013) in 32% of the market (FIEC, 2019) and all vehicles increased 2.3 times (J. Allwood & Cullen, 2013) in the entire market. This increase in lifetime is modelled by reducing the size of transactions proportionally. Therefore, longer life means fewer sales of a specific product. Furthermore, repairing and maintenance services are increased proportionally according to the intervention.

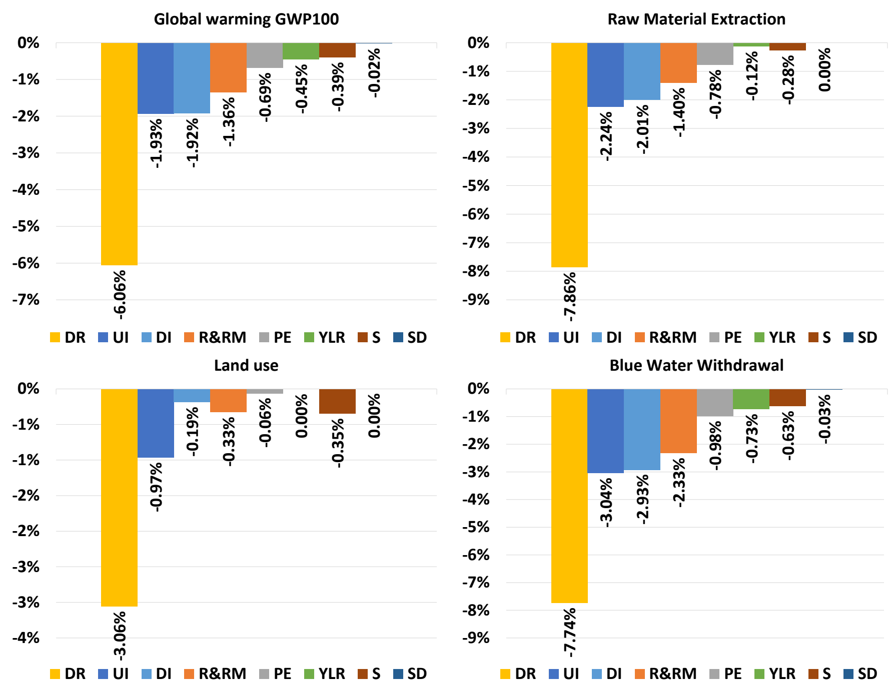


Figure 6: Global relative change in environmental indicators due to the individual Circular Economy Interventions. Labels: DR = Delayed Replacement; UI = Use Intensification; DI = Design Improvements; R&RM = Reuse and Remanufacturing; PE = Process Efficiency; YLR = Yield Loss Reduction; S = Sharing; SD = Scrap Diversion

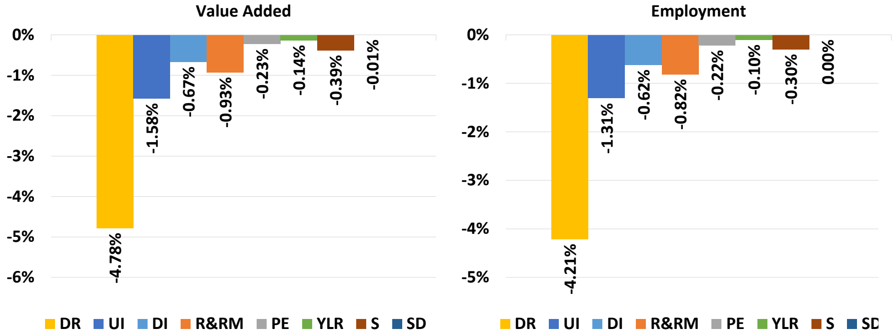


Figure 7: Global relative change in socio-economic indicators due to the individual Circular Economy Interventions. Labels: DR = Delayed Replacement; UI = Use Intensification; DI = Design Improvements; R&RM = Reuse and Remanufacturing; PE = Process Efficiency; YLR = Yield Loss Reduction; S = Sharing; SD = Scrap Diversion

Reuse and remanufacturing on the other hand, while less meaningful than delayed replacement, may still deliver significant environmental benefits (-1.36% GWP; -1.40% RME; -0.33% LU; -2.33% BWW) at a lower burden on employment (-0.93%) and value added (-0.82). However, our input data concerned mostly the reuse and remanufacturing of components for industrial or infrastructural purposes (e.g. refurbishing electricity transmission components), with only a few interventions affecting final consumer goods (e.g. reuse of parts in vehicles and mechanical products). Therefore, while we show environmental impact reduction, this cannot be considered a rule for all cases of reuse as discussed also by (Cooper & Gutowski, 2015) and effects may differ depending on the region (Duchin & Levine, 2019).

Use intensification and Design improvements appear to be the most effective RE interventions under all environmental indicators, followed by Process efficiency. In particular, changes in GWP amounted to: -1.93% Use intensification; -1.92% Design Improvements; -0.69% in Process Efficiency; -0.45% in yield loss reduction; -0.39% Sharing and -0.02% in scrap diversion.

Covering how vehicles, buildings and machineries are used on a daily basis - and their maintenance and reparation - use intensification's environmental benefits also appear to be substantial (-1.93% GWP; -2.24% RME; -0.97% LU; -3.04% BWW). However, these environmental benefits rely on the assumption that production is avoided due to a more intensive use. Followed by this category, we find design improvements, concerned the reduction of material used during the production of various transport methods (-53%), structural construction components (-29.4%), and mechanical and electrical equipment (-34%). This was modelled by reducing the amount of steel and aluminum during manufacturing (Annex I.a). It is important to note that we did not take into account other types of design improvements concerning better performing components or design for disassembly, which may influence emissions during the use phase as well as enabling availability of scrap at the end of life.

Process improvements concerns only the application of additive manufacturing. We assumed that 28% (Fraunhofer-Gesellschaft, 2018) material savings are obtained by using additive manufacturing for steel and aluminum in the production of parts for the transport sector, precision tools, and mechanical and electrical equipment. Due to lack of data on the potential market penetration, we assumed that this process improvement would affect the entire production.

Yield loss reduction intervention also indicates some environmental benefits (-0.45% GWP; -0.12% RME; -0.73% BWW) except for LU which remained unchanged. Also socio-economic indicators were moderately reduced (-0.14 VA and -0.10 E). This intervention was modelled by assuming that a cumulative 35% of steel and aluminum going to recycling processing from the production of semi-manufactured products is diverted to other uses instead.

The environmental benefits of Sharing appear moderate in comparison with the other interventions (-0.39% GWP; -0.28% RME; -0.35% LU; -0.63% BWW). Also socio-economic indicators see a contraction (-0.39 VA and -0.30 E). Analyzing the specialized intervention we see that this is mainly due to the change in the way we travel - namely increasing occupancy and use of personal vehicles – and sharing machineries across industries. In particular the increase in occupancy of vehicles is most aggressive specialized intervention affecting environmental performance, which however also has the highest impact on socio-economic indicators. This is due to the fact that increasing occupancy of vehicles would negatively affect the demand on public transport.

At last, we see that the implementation of Scrap Diversion shows moderate reductions in environmental factors. This is mostly due to the limited scrap availability. For instance, while scrap diversion of steel and aluminum in the construction sector could be diverted by 90% (J. Allwood & Cullen, 2013), the availability of scrap from this use is only 7% (J. Allwood & Cullen, 2013). This leads us to consider that while this intervention may be a good practice and beneficial for individual manufacturing firms, their benefits on the global scale may be limited.

3.5 Discussion

3.5.1 Methods and framework

One of the aims of this paper was to propose standard EEIO modeling procedures for CE strategies and their interventions. We proposed a total of 10 interventions under two CE strategies. Although the basic CE strategies are in line with those found by Aguilar et al. (2018), we innovated by making a clear distinction between strategies and interventions. We also expanded the approach of Aguilar-Hernandez et al. (2018) by including components, services, and primary and secondary materials. These interventions' blueprints provide a large degree of flexibility in describing the relationships between various elements of IO tables. However, they need to be applied critically because, as shown in the case of sharing, variations may be needed depending on the specific case. Additionally, the blueprints do not discuss how trade should be modelled. Therefore, we are assuming that trade would change relative to the applied changes. This is an assumption that in some case may need to be modified. Furthermore, our modeling choices respond to the premise of creating static representations of a counterfactual economic structure using IO. As such, they do not take into account changes in price dynamics, investments and stocks. Concerning the use a static monetary IO system, we see that it limited our possibilities to model strategies for residual waste management. The use of dynamic models (e.g. CGE or Stock and flow consistent models) and hybrid unit IO data could provide respectively additional insights on monetary dynamics of the CE and the physical transaction and stocks creation in the global economy.

3.5.2 Software and Data

Open-access software and data was of great importance in our study. Our desire was to ensure study replicability and transparency. In our review we found some proprietary software and platforms that allowed for the simulation of interventions. However, they were specific to a few regions and in some cases the software or data was not publicly accessible. In particular, no Python packages were available that allowed for the transformation from SUTs to IO and for scenario modeling. We therefore developed pycirk, a Python package to handle EXIOBASE V3.3 and convert SUTs to IO tables to create scenarios for CE. Pycirk gives the opportunity to implement an indefinite number of changes in any matrix in the IO system. In this way, one can process multiple type interventions at ones, including substitutions. These features are useful in the creation and analysis of scenarios. Currently, pycirk only supports product-by-product industry-technology transformation. Furthermore, pycirk allows for the creation of EXIOBASE IO tables in which secondary raw material transactions are explicitly separated from primary raw materials. This is a unique feature that allows modelers to analyze secondary raw material production and consumption in EXIOBASE IO tables.

3.5.3 Case study

We performed a zero-cost analysis of a counterfactual economy using the EEIOA. Therefore, we presented a world in which CE strategies were already implemented. Investments and fiscal stimuli were not included. This means, that effects of material taxes and subsidies could not be investigated. For this reason, many of the other studies found focused on CGE models. Their advantage is in the ability to represent dynamic aspects of the economy. This comes at the expense of sectoral resolution, something for which EEIO as a structural model is better suited. For this reason many previous studies on CE are difficult to compare to our results.

For the interventions, strategies and goods that we investigated, various assumptions had to be made on the basis of EXIOBASE product category aggregation. For instance, the data collected (Annex I.a) often referred to products for which there was no explicit category in EXIOBASE and were therefore sub-items of an aggregated product category. Where it was possible we disaggregated the values by their relative market size, otherwise we made an average of the change coefficients to be applied. In order to provide a logical order of intervention processing, their schedule was optimized against the baseline. However, other types of scheduling may output different results (Annex I.g). Moreover, the study was conducted on a bi-regional global level, with EU and ROW as the only two regions, however, results at a country or regional level may differ greatly as also discussed by (Duchin & Levine, 2012) and (Wiebe et al., 2019).

Additionally, we did not take into consideration changes in commodity and service prices resulting from endogenous or exogenous factors. Changes in investment, reinvestment of savings due the increased efficiency and global market trends such as the transition to a renewable energy system and electrification of mobility were not considered. This differs from previous studies we analyzed which often presented analyses of the transition to a new CE state within a time range (EMF, 2015; WRAP, 2015; Wijkman and Skanberg, 2015; (Winning et al., 2017), Wiebe et al., 2019). In particular, the study by WRAP (2015) which concerned reuse, recycling, repair and remanufacturing and servitization in the UK, showed that by 2030 the circular economy could deliver an increase of employment between 31,000 and 517,000 people in the UK alone (0.1-2% from 2015 UK employment). Our results, while of different scope, show that in the EU (EU28) employment may decrease by 5.31%. In the study by Rutherford et al. (2015), provided an aggressive EU agenda on CE to 2050, reductions of 83% in CO2 emissions and an increase of 27% in value added could be seen in the EU (EU27). However, while our study shows a different picture, it is important to stress that we did not take into consideration the transition to a renewable energy system and changes in the food system while they did. Therefore, much more moderate impacts are seen on our results. In the study by Wijkman and Skanberg (2015), only one part could be compared to our work, the resource efficiency scenario. Although, the process efficiency improvement in their scenario (25%) is comparable to ours (28%), their other RE interventions appear more aggressive than in our case. Despite the differences in assumptions, their results show GWP reductions between 3 and 10% depending on the analyzed country, against our 10.1% global reductions. Furthermore, (Winning et al., 2017) showed -0.02% change in GWP due the doubling of scrap availability which appears to confirm our results concerning scrap diversion. Our results on material extraction (-

12.5%) are also above those seen in the work of Wiebe et al. (2019) (-10%). At the same, their results on employment are ~2% while we show -5.3%. The change in employment and value added seems to vary substantially across literature as shown also by McCarthy et al. (2018).

3.5.4 Future work

From a methodological perspective, intervention modeling blueprints should be further expanded and validated. Relationships concerning fiscal stimuli and rebound effects specific to interventions should also be established. The blueprints should be adapted to other types of IO models (e.g. hybrid unit) and to SUTs. The software could be instrumental in this by being expanded to allow changes on different types of data structures, using different types of datasets and transformation methods. This would allow modelers to run sensitivity analysis on their scenarios, something that was not possible to do with the current software. Future studies should also enrich our findings on CE so to provide a representation of CE closer to real world dynamics. In particular, more research is needed on the CE strategies and interventions that could not be investigated in our study. For instance, Closing Supply Chains and its potential interventions. Future work should provide additional insights on CE effects of many other interventions, product categories and their stocks across regions as well as more strongly integrating economic and physical material studies through the use of EEIOA.

3.6 Conclusions

We presented a framework, a software and a structural study on the Circular Economy (CE). The framework provides an overview of the structure of CE strategies and their implementation in EEIO. Modeling blueprints were used to aid scenario building and to provide a systematic and transparent application of interventions. We also presented pycirk, a free and open-source Python package for modeling policies, and technological and market changes in EEIO starting from the SUTs database EXIOBASE v3.3 for 2011. This is done chiefly to provide practitioners with tools to model CE policies in EEIOA in order to facilitate decision making in the transition to a sustainable society. The possibilities and use of pycirk were exemplified through a case study on the CE on a bi-regional (EU-ROW) IO system. Using this system, we created scenarios for 2 CE strategies: Product Lifetime Extensions and Resource Efficiency. The results from the case study show that environmental benefits can be obtained through the pursuit of CE strategies. In particular, the combined global effects could amount to a global relative change of -10.1% (GWP100), -12.5% raw material extraction used, -4.2% land use and -14.6% blue water withdrawal. The analysis of the socio-economic indicators showed global reductions of 6.3% in Value Added and 5.3% in Employment globally. However, it is to be noted that fiscal stimuli (subsidies or tax changes), investment and price changes were not included. For this reason, our approach did not follow the premise that a CE delivers equal or better economic performance. Additionally, an apparent change in GDP does not necessarily represent a loss of general wealth so long as the same utility is maintained. Nevertheless, the results from this case study should be used and interpreted with care as our scenarios aimed largely at show-casing the use of the methods and software presented.

SUPPLEMENTARY INFORMATION

Annex I and II: https://doi.org/10.5281/zenodo.7419203

References

Aguilar Hernandez, G.A., Sigüenza Sanchez, C.P., Donati, F., Rodrigues, J.F.D and Tukker A. (2018) 'Assessing circularity interventions: a review of EEIOA-based studies', *Journal of Economic Structures. SpringerOpen, 7*(1), p. 14. doi: 10.1186/s40008-018-0113-3.

Allwood, J. and Cullen, M.J. (2012) *'Sustainable materials – with both eyes open',* University of Cambridge - The Future in Practice. doi: 10.1179/0301923312Z.000000000103.

Charonis, G.-K. (2012) 'Degrowth, steady state economics and the circular economy: three distinct yet increasingly converging alternative discourses to economic growth for achieving environmental sustainability and social equity', in *Neoclassical economics as a driver for development*. World Economics Association (WEA) Conferences, No. 2 2012, Sustainability – Missing Points in the Development Dialogue, 24th September to 21st October, 2012, p. 12.

Cooper, D. R. and Gutowski, T. G. (2015) 'The Environmental Impacts of Reuse: A Review', *Journal of Industrial Ecology, 21*(1), pp. 38–56. doi: 10.1111/jiec.12388.

Donati, F. (2017) *CE_EEIOA.* 10.5281/zenodo.398850

Donati, F. (2018) *pickle_exiobase,* https://bitbucket.org/CML-IE/pickle_exiobase, doi:10.5281/zenodo.1490415

Donati, F. (2018) *pycirk,* https://pypi.org/project/pycirk/, doi:10.5281/zenodo.1492957

Donati, F. (2019) '*Pycirk - ReadTheDocs'. Leiden: Read The Docs*. Available at: https://pycirk.readthedocs.io/en/latest/readme.htm

Duchin, F. and Levine, S. (2012) 'The rectangular sector-by-technology model: not every economy produces every product and some products may rely on several technologies simultaneously', *Journal of Economic Structures, 1(1), p. 3*. doi: 10.1186/2193-2409-1-3.

Eisenmenger N., Theurl M., Gierlinger S., Giljum S., Lutter S., Bruckner M., Deetman S., Koning A., Kleijn R., Acosta J., Usubiaga A., (2014) *'Development of a System of Indicators for a Resource Efficient Europe (DESIRE) - D4.2 final report on indicator framework'*, 12(October 2013).

EMF (2012) Towards the Circular Economy. Economic and business rationals for an accelerated transition, Greener Management International *Ellen MacArthur Foundation*. doi: 2012-04-03.

EMF (2015) 'Growth within: a circular economy vision for a competitive europe', *Ellen MacArthur Foundation, p. 100*. doi: Article.

European Commission (2018) 'Report on Critical Raw Materials and the Circular Economy', *Commission Staff Working Document, (SWD(2018)36).*

Eurostat (2008) *Eurostat Manual of Supply, Use and Input-Output Tables*, Methodologies and working papers, Economy and finance. doi: http://ec.europa.eu/eurostat.

Faucheux, S. and Froger, G. (1995) 'Decision-making under environmental uncertainty', *Ecological Economics.* Elsevier, 15(1), pp. 29–42. doi: 10.1016/0921-8009(95)00018-5.

Fauré, E., Arushanyan, Y., Ekener, E., Miliutenko, S., Finnveden, G. (2017) 'Methods for assessing future scenarios from a sustainability perspective', *European Journal of Futures Research.* Springer Berlin Heidelberg, 5(1), p. 17. doi: 10.1007/s40309-017-0121-9.

FIEC (2019) *KEY FIGURES ACTIVITY 2018.* CONSTRUCTION IN EUROPE EDITION 2019

FP7 (2007) *Desire Project - Home.* Available at: http://www.desire-project.eu/ (Accessed: 10 September 2018).

Fraunhofer-Gesellschaft (2018) *'Efficient use of resources in manufacture of metal components'*, https://phys.org. Available at: https://phys.org/news/2018-02-efficient-resources-metal-components.html.

Frazier, W. E. (2014) 'Metal additive manufacturing: A review', *Journal of Materials Engineering and Performance*. doi: 10.1007/s11665-014-0958-z.

Geng, Y., Sarkis, J. and Ulgiati, S. (2016) 'Sustainability, wellbeing, and the circular economy in China and worldwide', *Science,* March(April), pp. 76–79.

Ghisellini, P., Cialani, C. and Ulgiati, S. (2016) 'A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems', *Journal of Cleaner Production*. doi: 10.1016/j.jclepro.2015.09.007.

Homrich, A. S., Galvão, G., Abadia, L. G., & Carvalho, M. M. (2018) 'The circular economy umbrella: Trends and gaps on integrating pathways', *JOURNAL OF CLEANER PRODUCTION, 175*, pp. 525–543. doi: 10.1016/j.jclepro.2017.11.064

Iacovidou, E., Velis, C.A., Purnell, P., Zwirner, O., Brown, A., Hahladakis, J., Millward-Hopkins, J. and Williams, P.T. (2017) 'Metrics for optimising the multi-dimensional value of resources recovered from waste in a circular economy: A critical review', *Journal of Cleaner Production.* Elsevier Ltd, 166, pp. 910–938. doi: 10.1016/j.jclepro.2017.07.100.

IPCC (2007) '*Climate change 2007: the physical science basis'*, Intergovernmental Panel on Climate Change. doi: 10.1038/446727a.

Kang, S., Kim, J. J. and Masui, T. (2006) '*A National CGE modeling for Resource Circular Economy'*, pp. 1–90.

Knights, A.M., Culhane, F., Hussain, S.S., Papadopoulou, K.N., Piet, G.J., Raakær, J., Rogers, S.I. and Robinson, L.A. (2014) 'A step-wise process of decision-making under uncertainty when implementing environmental policy', *Environmental Science & Policy.* Elsevier, 39, pp. 56–64. doi: 10.1016/J.ENVSCI.2014.02.010.

de Koning, A. (2018) *Creating global scenarios of environmental impacts with structural economic models*. PhD. Thesis, Leiden University, Leiden, Netherlands. isbn:9789490858551.

Kronen, M., Vunisea, A., Magron, F. and McArdle, B. (2010) 'Socio-economic drivers and indicators for artisanal coastal fisheries in Pacific island countries and territories and their use for fisheries management strategies', *Marine Policy, 34*(6), pp. 1135–1143. doi: 10.1016/j.marpol.2010.03.013.

Leontief, W. W. (1951) The Structure of the American Economy, 1919-1939: An Empirical Application of Equilibrium Analysis, *Econometrica*. Harvard University Press. doi: 10.2307/1906819.

Leontief, W. W. (1970) 'Environmental Repercussions and the Economic Structure: An Input-Output Approach', *The Review of Economics and Statistics, 52*(3), pp. 262–271. doi: 10.2307/1926294.

Li, S. (2012) 'The Research on Quantitative Evaluation of Circular Economy Based on Waste Input-Output Analysis', *Procedia Environmental Sciences, 12*, pp. 65–71. doi: 10.1016/j.proenv.2012.01.248.

Lieberman, M. (2015) *Pwc-Consumer-Intelligence-Series-the-Sharing-Economy, PWC Consumer Intelligence Series: The Sharing Economy.*

McCarthy, A., Dellink, R. and Bibas, R. (2018) The Macroeconomics of the Circular Economy Transition: A Critical Review of Modelling Approaches, *OECD Publishing*. 130. Paris. doi: https://doi.org/10.1787/af983f9a-en.

Merciai, S. and Schmidt, J. (2018) 'Methodology for the Construction of Global Multi-Regional Hybrid Supply and Use Tables for the EXIOBASE v3 Database', *Journal of Industrial Ecology.* doi: 10.1111/jiec.12713.

Miller, R. E. and R.D. Blair (2009) *'Input–Output Analysis Foundations and Extensions'.* Cambridge, UK: Cambridge University Press

Nakamura, S. and Kondo, Y. (2009) *Waste Input-Output Analysis. Dordrecht: Springer Netherlands Eco-Efficiency in Industry and Science.* Available at: http://link.springer.com/10.1007/978-1-4020-9902-1.

Nazara, S., Guo, D., Hewings, G. and Dridi, C. (2004) *PyIO: Input-Output Analysis with Python. User Manual*. Available at: http://www.uiuc.edu/unit/real/.

Rizos, V., Tuokko, K. and Behrens, A. (2017) *The Circular Economy A review of definitions, processes and impacts*. CEPS Research Report No 2017/8. Available at: https://www.ceps.eu/system/files/RR2017-08_CircularEconomy_0.pdf.

Sacchi-Homrich, A. et al. (2018) 'The circular economy umbrella: Trends and gaps on integrating pathways', *JOURNAL OF CLEANER PRODUCTION, 175*, pp. 525–543. doi: 10.1016/j.jclepro.2017.11.064.

Stahel, W. R. (2016) 'Circular Economy', *Nature, 531*(7595). doi: 10.1038/531435a.

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M. and Owen, A. (2016) 'Decoupling global environmental pressure and economic growth: scenarios for energy use, materials use and carbon emissions', *Journal of Cleaner Production.* doi: 10.1016/j.jclepro.2015.06.100.

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J.H., Theurl, M.C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., de Koning, A., Tukker, A. (2018).EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *Journal of Industrial Ecology, 22*(3) 502-515

Suh, S. (2009) *Handbook of Input-Output Economics in Industrial Ecology, Eco-Efficiency in Industry and Science.* Edited by S. Suh and A. Tukker. Dordrecht: Springer Netherlands (Eco-Efficiency in Industry and Science). doi: 10.1007/978-1-4020-5737-3.

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R. and de Vries, G.J. (2015) 'An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production', *Review of International Economics, 23*(3), pp. 575–605. doi: 10.1111/roie.12178.

Tisserant, A. et al. (2017) 'Solid Waste and the Circular Economy: A Global Analysis of Waste Treatment and Waste Footprints', *Journal of Industrial Ecology*. doi: 10.1111/jiec.12562.

Tukker, A. et al. (2013) 'Exiopol – Development and Illustrative Analyses of a Detailed Global Mr Ee Sut/Iot', *Economic Systems Research, 25*(1), pp. 50–70. doi: 10.1080/09535314.2012.761952.

UNEP (2011) *'Decoupling Natural Resource Use and Environmental Impacts from Economic Growth'*, in International Resource Panel.

Wiebe, K. S. et al. (2019) 'Global Circular Economy Scenario in a Multiregional Input–Output Framework', *Environmental Science & Technology.* doi: 10.1021/acs.est.9b01208.

Wijkman, A. and Skanberg, K. (2015) *The Circular Economy and Benefits for Society.* The club of Rome.

Winning, M., Calzadilla, A., Bleischwitz, R. and Nechifor, V. (2017) 'Towards a circular economy: insights based on the development of the global ENGAGE-materials model and evidence for the iron and steel industry', *International Economics and Economic Policy. Springer Berlin Heidelberg, 14*(3), pp. 383–407. doi: 10.1007/s10368-017-0385-3.

Wood, R., Stadler, K., Bulavskaya, T., Lutter, S., Giljum, S., de Koning, A. and Tukker, A. (2015) 'Global sustainability accounting-developing EXIOBASE for multi-regional footprint analysis', *Sustainability (Switzerland), 7*(1), pp. 138–163. doi: 10.3390/su7010138.

Wood, R., Moran, D., Stadler, K., Ivanova, D., Steen-Olsen, K., Tisserant, A., and Hertwich, E. G.. (2017) 'Prioritizing Consumption-Based Carbon Policy Based on the Evaluation of Mitigation Potential Using Input-Output Methods', *Journal of Industrial Ecology*. doi: 10.1111/jiec.12702.

WRAP (2015) *'Employment and the Circular Economy | WRAP UK'*, WRAP, 2. October.

Yifang, L. (2007) 'The Input-Output Analysis of the Circular Economy', *16th International Input-Output Conference*, 2-6 July 2007.

4 MODELING THE CIRCULAR ECONOMY IN ENVIRONMENTALLY EXTENDED INPUT-OUTPUT: A WEB-APPLICATION

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ABSTRACT

Global environmental and resource problems ask for new ways of managing the production and consumption of resources. The implementation of new paradigms, such as the circular economy, require decision makers at multiple levels to make complex decisions. For this, clear analyses and modelling of scenarios are of utmost importance. Meanwhile, as the sophistication of database and models increases so does the need for user-friendly tools to use them. The RaMa-Scene web-platform reduces these barriers by allowing users to visualize easily diverse impacts of implementing circular economy interventions. This online web-platform makes use of the multi-regional Environmentally Extended Input-Output database EXIOBASE version 3 in monetary units, which has been modified to show explicit transactions of raw materials from recycling activities.

KEYWORDS

Circular Economy, Ecological Economics, Environmental Input–Output Analysis (EEIOA), Industrial Ecology, Internet-based Modeling, Scenario Analysis

4.1 INTRODUCTION

Environmental, economic and social global implications of a transition to a circular economy (CE) remain to this day difficult to assess. While scientists and practitioners have studied the benefits and drawbacks of scenarios of changes of implementing CE strategies, results give conflicting information (Donati et al. 2020 and McCarthy et al., 2018 and references therein, and Aguilar-Hernandez et al., 2021). More research is needed to support decision makers with robust advice (McCarthy et al., 2018). There are challenges in the incorporation of environmental impact assessment tools into decision making (Jay et al., 2007), in the participation of stakeholders in environmental modelling (Voinov et al., 2016), in the sharing and handling of multi-disciplinary data (Davis et al., 2010) and replicability of outputs (González et al., 2019). These challenges and the lack of availability of user-friendly tools for the creation of global scenarios, hinder the objective of providing clear and robust guidance on CE strategies.

Economists and environmental scientists tried to overcome these barriers by developing tools for the analysis of the impact of policy interventions and technological changes. In particular, native (i.e. to be used on specific systems) and web-based tools for macro-level environmental impact assessment have been developed. As we will discuss later in this paper, at this point in time none of these tools are well suited to assess environmental and economic implications of CE interventions.

Therefore, in order to support easy access to economic and environmental information and to reduce barriers for scenario creation, we developed a web-based application, *RaMa-Scene* (RAw MAterials SCENario Efficiency improvement assessment tool). RaMa-Scene combines strengths of previous platforms and provides additional features for analyzing and modelling scenarios in the monetary multi-regional environmental extended input-output (mrEEIO) database EXIOBASE. The web-platform is accessible by visiting www.ramascene.eu.

In the following sections, we describe the requirements we defined for such a web-tool in relation to what existing platforms offer (section 2); how the data, methods and interface of the Rama Scene platform was constructed (section 3); use-cases to illustrate the use of the platform (section 4); discussion and conclusions (section 5).

4.2 Requirements, review of existing software, and design choices for Rama Scene

The development of the software started with an inventory of requirements. A consultation with potential users highlighted the following as essential:

1. Ease of access and use were important factors for the facilitation of CE insights creation by multiple types of users;
2. The possibility for user modification of input data to see the effects CE interventions;
3. The ability to intervene also in secondary raw materials supply chains together with a high sectoral resolution, since CE focuses strongly on resource management;
4. Comparability of the current economic status to possible scenarios, as the CE is composed by multiple strategies and interventions (Donati *et al.*, 2020).

To avoid repeating work, we initially screened a number of web-based and native software against these criteria (see section 2.1). From there, we made decisions about the design strategy for the Rama-Scene platform (see section 2.2)

4.2.1 Review of existing software

Our software review was created by online search and inputs from potential users. We investigated a variety of tools used in four main interest areas in the industrial ecology community, namely Life-Cycle Assessment, Material Flow Analysis, Environmentally Extended Input-Output Analysis and, more generally, sustainability assessment tools. Additionally, under indication of users we added tools which they considered note-worthy. In this phase, we identified 27 applications (see the Supporting Information in Annex I). Of these 27 applications, 9 provided scenario creation features of which 6 included macro or structural economic data at the global level. The rest of the software had specific focus (e.g. construction or aviation sector), or did not provide the possibility to create global and national scenarios (e.g. trade data visualizers), or required users to provide product level information (e.g. life-cycle assessment tools). The following review describes 6 applications (web links available in SI, except EUREAPA), which could provide analysis of global economic data and environmental impacts, and features to create scenarios. The analysis focuses on the aforementioned criteria of availability of materials from secondary sources in the database, scenario-modelling features, accessibility and user-friendliness.

Nazara et al. (2004) created a free and open-source Python-2 based software named REAL pyIO. The software has multiple functionalities allowing users to analyze in depth IO data using advanced methods including the Ghosh model (Ghosh, 1958) and the RAS method (Stone, 1962) which is used for balancing and projecting IO tables. Users can visualize and modify the IO database of their choosing provided that it can be copied into the software integrated spreadsheet. The software does not offer data visualization features and it is aimed at a specialized audience.

Carnegie Mellon's EIO-LCA (GDI, 2008) is a free and open source web platform that can be used to analyze policy impacts using USA and international Input-Output (IO) datasets up to 2007. The tool allows for the estimation of environmental impacts and energy for national economies through a simple yet intuitive interface. The tool allows creating scenarios by editing both final demand and industrial transactions. Scenarios are obtained by defining a production recipe for a new product or modifying a pre-existing one. Users are presented with a list of all the inputs that can be modified in absolute terms and they can then visualize results by means of simple pie-charts.

EUREAPA (Roelich et al., 2014) was a free-access web-tool employing IO data based on GTAP7 (McDougall & Golub, 2007) which is no longer accessible. It allowed for the analysis of pre-calculated future scenarios in the context of dietary, transport, and energy policies, affluence and population changes. The different scenarios were created with the support of specialists. Thus, users had control over the intensity of a policy intervention based on expert information. It presented a simple and intuitive interface in which drop down menus allowed users to make selections of different elements for analysis to be displayed on a bar-graph.

pyMRIO is a Python package that allows using most available multi-regional EEIO databases to perform various types of IO analyses, including scenario building and visualizations (Stadler, 2018). Functionalities include aggregation, extension restructuring and footprint analysis.

Pycirk (Donati, 2019a) is a free and open-source Python-3 package for the analysis and modelling of the mrEEIO database EXIOBASE after transformation from mrEESUTs (multi-regional Environmentally Extended Supply-Use Tables). The package allows for creating scenarios by modifying values in any table in the database, including secondary raw materials transactions. Additionally, it allows for extensive selection of analytical parameters (e.g. extensions) for the result output. Thanks to a standardized format, scenario settings and results can be easily saved and replicated. Although without visualization features, users can easily compare different results by operating the software through a command line. Pycirk is aimed at mrEEIO practitioners with programming experience.

IOsnap (Jackson & Court, 2019) is a Windows-native commercial software for the analysis and modelling of USA IO data. The software interface allows the user to analyze economic impacts at different regional level. Scenarios are created by absolute changes in the final demand of 11 available sectors. The software presents a simple interface aimed at a specialized audience.

IMPLAN (IMPLAN, 2018) is a widely used commercial web-based tool for the analysis of IO data. The tool has an advanced, however, simple interface for the analysis of economic impacts at the level of 400 sectors in the USA. The data is highly disaggregated at the regional level. The tool has functionalities for scenario making at both final demand and industrial level (i.e. production recipe), integrating also indirect impact assessment capabilities.

None of the tools offered a free and open-source online option for the analysis of the impacts of CE. In fact, only the Carnegie Mellon’s EIO-LCA platform allowed for the modification of production recipes (GDI, 2008) but it was not in global multi-regional form. REAL PyIO and Pycirk, allowed for the modification of multi-regional IO databases of which only one (Donati et al.) included the assessment of a diverse set of environmental extensions. UK’s 2050 Global calculator and EUREAPA allowed for the analysis of pre-calculated scenarios for different types of policies (HM Government, 2010;

Roelich et al., 2014), however they did not permit interactive exploration or direct modifications of the database. Two tools, IOsnap (native) and IMPLAN (web-app), presented modelling features at final demand or final demand and intermediate level. However, both tools were commercial, which represents a barrier in accessibility of data and results by a broader community.

As previously discussed, these last two features are fundamental for offering users different options for the assessment and modelling of improvements of CE interventions.

4.2.2 Implications and design choices for the RaMa-Scene platform

Given that no current platform met our requirements, the decision was made to develop a dedicated platform.

Firstly, to ensure ease of access and use, we decided to develop a web-platform with a user-friendly interface. The design of the interface and the visualizations are inspired by previously developed web-tools such as the Atlas of Economic Complexity (Hausmann et al., 2019), thereby facilitating the use of results across multiple platforms providing different economic insights.

Secondly, visualization of results should be presented side by side so that users can rapidly see the difference from baseline and scenarios thereby facilitating comparability (see also section 3).

Thirdly, since a high sectoral resolution was essential to model CE interventions, we decided to use the EXIOBASE database. At the time of writing this study, EXIOBASE is the IO database with the largest number of available sectors and presents detailed environmental and socio-economic information of sectors and regions globally across multiple years (Stadler, Wood, Bulavskaya, Södersten, Simas, Schmidt, Usubiaga, Acosta-Fernández, Kuenen, Bruckner, Giljum, Lutter, Merciai, Schmidt, Theurl, Plutzar, Kastner, Eisenmenger, Erb, de Koning, et al., 2018; Wood et al., 2015). The additional advantage of employing EXIOBASE is the presence of data concerning secondary raw-materials transactions (Merciai & Schmidt, 2018).

Lastly, in order to allow for the assessment of CE interventions, a dedicated feature for the modification of the underlying data should be present. The EIO-LCA tool (GDI, 2008) and Pycirk (Donati et al.) are good examples of implementation of this feature.

4.3 Data, Methods and User Interface

In this section, we describe the database and methods used in the calculation of the IO system, data-selection and scenario creation.

4.3.1 Data

RaMa-Scene employs the monetary mrEEIO database EXIOBASE version 3.3.sm (Donati & Koning, 2019) in product-by-product Industry-technology assumption format (Miller & Blair, 2009). It includes a 16 year time range (1995-2011), 49 regions, 200 product categories concerning commodity and services, 1 aggregate final demand category and 60 environmental and socio-economic extensions characterized to 10 footprint indicators. This version of EXIOBASE differs from the official release of EXIOBASE v3 (Stadler, Wood, Bulavskaya, Södersten, Simas, Schmidt, Usubiaga, Acosta-Fernández, Kuenen, Bruckner, Giljum, Lutter, Merciai, Schmidt, Theurl, Plutzar, Kastner, Eisenmenger, Erb, de Koning, et al., 2018) as some extensions have been excluded (e.g. water accounts) while others have been characterized into impact indicators. Additionally, the 7 final demand categories of EXIOBASE were aggregated into one and the database was modified to make secondary raw materials (SM) available in the IO system. Typically, there is no SM sector in the product-by-product IO tables because the output of end-of-life recycling is aggregated into primary materials. This meant that the Input-Output lacked that information after transformation from Supply-Use tables (SUTs). Faced with this challenge, other authors have employed hybrid tables using a Waste Input-Output model (Aguilar-Hernandez et al., 2018c). The decision to employ monetary data, instead of hybrid data, was based on technical constraints and information preferences. The difference in units among the different commodities of the hybrid tables of EXIOBASE increases complexity both for the technical display of data but also in the phase of scenario data collection as market information appears to be more readily available. Furthermore, the hybrid data does not contain information on value added and employment studies (Merciai & Schmidt, 2018) which are important indicators to ensure comparability of analysis to previous studies (McCarthy et al., 2018). Therefore, we employed EXIOBASE monetary IO tables which have been modified with the method presented by Donati *et al.* (2020) in the supplementary information. This method modifies the structure of the SUTs in a way that upon transformation to IO tables, SM (i.e. output from end-of-life recycling) become available. This database is named EXIOBASE V3.3.sm where "*sm*" stands for *Secondary raw Materials*[1].

4.3.2 Methods

One of the requirements was that of being web-based so that different types of users can easily access the tool. We could follow two development options: 1) pre-calculated scenario results; 2) on-the-fly calculation of results. The former requiring developers to create a number of scenarios from which the users could choose. The latter, providing the user with full flexibility of how CE interventions are implemented in the IO system. Given the variety in modelling CE interventions and in the analysis of CE dimensions, on-the-fly calculation of results was the preferred option. In this way, users can easily investigate and compare multiple dimensions of the database and CE interventions instead of being limited to options decided a priori by the developers. In particular, we allow for two types of analysis (hotspot and contribution analysis) and for the modification of IO transactions at the industrial and final demand levels. The following sections present these methods.

The Environmentally Extended Input-Output model

The mathematical model at the core of the platform is the final-demand-driven Environmental Input-Output model (Leontief, 1970b) described by the following equation:

$$r = b'Ly \tag{1}$$

[1] https://doi.org/10.5281/zenodo.3533196

Here endogenous scalar *r* represents the total amount of environmental (or other type of) impacts that results from the stimulus generated by the consumption bundle represented in column vector y. The parameters of the model are a column vector b (with ' denoting transpose) of intensities of the appropriate environmental extension (direct impact per unit of production) and matrix$L$, the Leontief inverse matrix. The latter is calculated by

$$L = (I - A)^{-1} \quad (2)$$

Where$I$ is the identity matrix and A is the technical coefficient matrix. Entry A_{ij} represents the purchase of inputs from i required to satisfy one unit of output of$j$.

The generalized equation 1 can also be expanded to represent the mrEEIO system used in RaMa-Scene.

$$\begin{matrix} \mathrm{r}_1 \\ \mathrm{r}_2 \\ \mathrm{r}_3 \end{matrix} = \begin{pmatrix} \boldsymbol{B}_{11} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{B}_{22} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{B}_{33} \end{pmatrix} \cdot \left(\boldsymbol{I} - \begin{pmatrix} \boldsymbol{A}_{11} & \boldsymbol{A}_{12} & \boldsymbol{A}_{13} \\ \boldsymbol{A}_{21} & \boldsymbol{A}_{22} & \boldsymbol{A}_{23} \\ \boldsymbol{A}_{31} & \boldsymbol{A}_{32} & \boldsymbol{A}_{33} \end{pmatrix} \right)^{-1} \cdot \begin{pmatrix} \boldsymbol{Y}_{11} & \boldsymbol{Y}_{12} & \boldsymbol{Y}_{13} \\ \boldsymbol{Y}_{21} & \boldsymbol{Y}_{22} & \boldsymbol{Y}_{23} \\ \boldsymbol{Y}_{31} & \boldsymbol{Y}_{32} & \boldsymbol{Y}_{33} \end{pmatrix} \cdot \boldsymbol{i} \quad (3)$$

Here, $\mathbf{Y}$ and $\mathbf{A}$ are matrices composed by multiple regions and i is a one vector of appropriate length used to transform $\mathbf{Y}$ into a vector y. $\mathbf{Y}$ and $\mathbf{A}$ diagonal transactions represent domestic consumption for each country and off-diagonal transactions are import (vertically) and export (horizontally). Each regional entry is composed by all product categories. For simplicity, all equations in the following sections refer to the generalized equation 1, however, knowing that they can be expanded to represent the multi-regional system.

Hotspot and contribution analyses

Consumption activities across all sectors and regions in the world cause environmental and socio-economic impacts. For this reason, it is often of interest to view in isolation impacts across only some of these dimensions. From the defined requirements we decided to allow for the visualization of the impacts of CE interventions using two standard analyses. In the *hotspot analysis*, impacts are discriminated based on the sectors and/or regions where they take place, irrespective of the final product delivered by the supply chain. In the *contribution analysis*, the total impacts occurring along the supply chain of a bundle of consumption products are discriminated by product category and/or the consuming region, irrespective of where those impacts occur along the supply chain.

Therefore, in the particular visualizations provided by RaMa-Scene, we are not interested in the 0-dimensional grand total r described in the previous equations but we want to have the 1-dimensional breakdown of impacts by either the sectors/regions where impacts occur (hotspot analysis) or the products/regions with the highest embodied impact (contribution analysis). These are obtained by adapting Equation 1 such that the vector on either the left or the right hand side of the Leontief inverse matrix is diagonalized. That is, a hotspot analysis is obtained as

$$r_h = diag(b)Ly \tag{4}$$

And a contribution analysis as

$$r_c = b'L\, diag(y) \tag{5}$$

Where $diag$ represents a diagonal matrix.

Sectoral and regional detail

As mentioned previously, we employ a mrEEIO model of the global economy which distinguishes a number of regions each with a number of economic sectors. In order to allow the user to investigate regional or a sectoral distribution of impacts, we provide an aggregation method for results with the complementary dimension (sectors or regions) being collapsed to a single item.

The multi-regional database is composed by $n_R$regions and n_S sectors per region. In either case, the result of IO calculations must be transformed so that a vector with n_D elements is displayed. These are obtained by applying an appropriate aggregation vector g and an appropriate selection matrix S. An aggregation vector is a column vector that has one or more entries with value 1 and the remainder entries zero. A selection matrix has n_D rows and either n_R or n_S columns, depending on the visualization detail, with one entry with value 1 per row, and at most one entry with value 1 per column and the remainder entries zero. The selection matrix defines the transformation between the full list of sectors or regions and the sectors or regions to display in the visualization. The aggregation vector defines the transformation of the full list of the complementary dimension (regions or sectors) to be the single item to display. Note that the control variable y in Equation 1 can be multiple things depending on the specific application of the model. However, in the construction of baseline scenarios it will be based on matrix Y, which is the matrix of final demand observed in the reference year, with n_R columns (one per region) and $n_R n_S$ rows (one per region and sector).

In the context of mrEEIO the impacts of consumption can be broken down along a total of 3 types of region and 2 types of sector coordinates. We summarized them by:

- the region where impacts occur;
- the sector where impacts occur;
- the region that delivers the product to final demand;
- the sector (or product) consumed by final demand;
- and the region of final demand.

RaMa-Scene allows for four combinations of analysis/detail, where each extracts a *vector* along a particular dimension among those five, with the complementary dimension characterized by a *set* along another, and *all* impacts are accounted for along the remainder dimensions. Table 1 summarizes this information. Note that in principle, there is yet another dimension along which the mrEEIO impacts of consumption could be distinguished, the final demand category, but in the database underlying RaMa-Scene this dimension has been collapsed to a single value.

Table 1: Break down of possible impacts of consumption (Geo = geographic)

	Analysis		Hotspot		Contribution	
	Detail		Sectoral	Geo	Sectoral	Geo
Dimensions	Sector	(Impact Occurs)	Vector	Single	All	All
	Region	(Impact Occurs)	Single	Vector	All	All
	Sector	(Delivers Product)	All	All	Vector	Single
	Region	(Delivers Product)	All	All	All	All
	Region	(Final Consumption)	All	All	Single	Vector

The four combinations of analysis/detail are obtained as variations of Eq.3-4 to account for the multi-regional nature of the system, combined with applications of$g$ and S and appropriate reshaping of vectors and matrices.

To obtain hotspot analyses with a sectoral or regional detail, first Eq.3 is applied with the stimulus vector being the row sum of total final demand, that is $y = Yi$, where i is a column vector of ones. The resulting vector r_h is then reshaped to a matrix R_h, with $n_S$rows and n_R columns, such that the (*ij*) entry of R_h, represents the impact in sector i and region j. The sectoral detail (θ_h^{sec}) is obtained by applying the aggregation vector to regions (right multiplication) and the selection matrix to sectors (left multiplication), thus:

$$\theta_h^{sec} = SR_hg \tag{6}$$

The regional detail θ_h^{reg} of the hotspot analysis is obtained by swapping the left and right multiplication of the aggregation vector and selection matrix:

$$\theta_h^{reg} = g'R_hS' \tag{7}$$

Note that the selection matrix is transposed since it is assumed that it has the desired classification in rows.

The contribution analysis begins through a multi-regional variation of Eq.4 but now the sequence of application of the aggregation vector and selection matrix is more complex. That is because the columns of final demand define the region of final consumption, whereas the rows of final demand define the sector.

The sectoral detail of the contribution analysis (θ_c^{sec}) is obtained by first applying Eq.4 where $y = Yg$, that is, aggregation along the complementary dimension occurs upfront. The resulting vector r_c is is then reshaped to a matrix R_c, with n_S rows and n_R columns, such that the (ij) entry of R_c represents the impact of the consumption of sector i originating from region j. The sectoral detail (θ_c^{sec}) is then obtained by summing over all regions (right multiplication) and applying the selection matrix to sectors (left multiplication), thus:

$$\theta_c^{sec} = SR_cI \tag{8}$$

The logical starting point for the calculation of the regional detail of the contribution analysis is to apply the selection matrix to the matrix of final demand, YS'. However, the resulting object is itself a matrix so Eq.4 cannot be applied. We need to write down a variation thereof:

$$R_c = diag(b'L)YS' \tag{9}$$

Matrix R_c has $n_R n_S$ rows and n_D columns, and entry (ij) represents the impact of consumption in region $j$of product k purchased from region l, where$i = k + (l-1)n_s$where it is assumed that counting start at 1 and sectors are nested within regions. Matrix R_c has to be reshaped in two steps so that entries along the dimensions of region of delivery and sector are aggregated. Formally this can be performed as follows. R_c is transformed into R_c^*, with n_R rows and $n_S n_D$ columns, whose entry (ij) represents the impact of consumption in region $l$of product k purchased from region i, where $j = k + (l-1)n_s$. Aggregation over the delivering region is performed as:

$$(r_c^*)' = i'R_c^* \tag{10}$$

This vector can now be reshaped as Matrix $R_c^{**}$with n_S rows and n_D columns, with entry (ij) representing the impact of consumption in region j of product i. Finally, the regional detail of the contribution analysis is obtained by the aggregation over the complementary dimension as:

$$\theta_c^{reg} = g'R_c^{**} \tag{11}$$

This concludes the four set of calculations used for the creation of visualizations.

4.3.3 Baseline and Counterfactual scenarios

The starting point to model a CE intervention is to have a snapshot of the real world, i.e., a baseline scenario of a year chosen by the user. From that baseline, CE interventions are modelled by a series of changes in coefficients of the model, leading to a counterfactual scenario.

RaMa-Scene uses the monetary mrEEIO system for a specific year chosen by the user as base to create scenarios by changing transactions in $\mathbf{Y}$ and $\mathbf{A}$. This means changing final consumption patterns ($\mathbf{Y}$) or production recipes ($\mathbf{A}$). The counter-factual (i.e. modified) mrEEIO system is then obtained by the following generalized equation:

$$\mathbf{r}^* = \mathbf{B}\mathbf{x}^* = \mathbf{B}(\mathbf{I} - \mathbf{A}^*)^{-1}\mathbf{Y}^* \cdot \mathrm{i} \tag{12}$$

Where * denotes a counterfactual matrix, $\mathbf{r}^*$ is the counterfactual vector of extensions obtained after the creation of the counterfactual final demand $\mathbf{Y}^*$ and the counterfactual Leontief inverse $\mathbf{L}^*$. The former is obtained modifying the matrix $\mathbf{A}$ to $\mathbf{A}^*$ and then calculating $\mathbf{L}^*$ as shown in equation 2**.**

Users of RaMa-Scene have nearly unlimited possibilities for the creation of counterfactual scenarios. However, while it is easy to modify values in the IO system, the most challenging aspects in scenario creation are collecting and organizing the new input data. In particular, users are recommended to consider the following aspects:

1. Primary impacts of an intervention (e.g. increase in sharing activities may results in a change in sales of goods while also affecting the use of services)
2. Potential ancillary changes needed to support the implementation of said intervention (e.g. changes in recycling may need changes in labor or in scrap and waste collection)
3. Commodity prices and their geographic differences (e.g. 1 kg copper may have a different price than 1 kg of aluminum and these prices may change depending on the region)

As shown, the counterfactual scenario in which CE interventions are implemented is constructed by editing elements of the A and Y matrices. Any element thereof can be chosen and a relative change (increase or decrease in percent) can be implemented. While this gives many opportunities for scenario creations, users need to keep in mind that RaMa-Scene does not perform any automatic balancing. This choice was motivated by the need to offer a quick response time of the tool and balancing would have increased computational requirements. Thus, if the user wants to perform the analysis of a scenario resulting in one or more sums of the inputs being $\neq 1$, then the IO system would remain unbalanced. Therefore, while users enjoy large freedom in the changes they apply to the system, they also need to be mindful of the way they construct their scenarios. In particular, users should consider whether they have included all needed coefficient changes due to the intervention, potential price changes and whether this difference is due to variation in value added. However, it is important to reassure users that while there may be a discrepancy between the sum of inputs and that of outputs, the total product output x is the reference vector for the recalculation of the extensions. This is to say that if an unbalanced system is presented, it will not affect the legitimacy of results of the environmental extensions. However, the categories forming value added - namely compensation of employees, subsidies and taxation – would need to be analyzed critically to avoid over- or underestimation of the socio-economic impacts. In the following section, we show how these methods were developed into the RaMa-Scene platform.

4.3.4 The Rama-Scene user interface

The user interface consists of six panels (fig 1). The first five are used to generate and visualize the baseline and counterfactual scenarios, and the sixth is a hub connecting to other online tools. We now list the actions that can be performed in each of the first five panels.

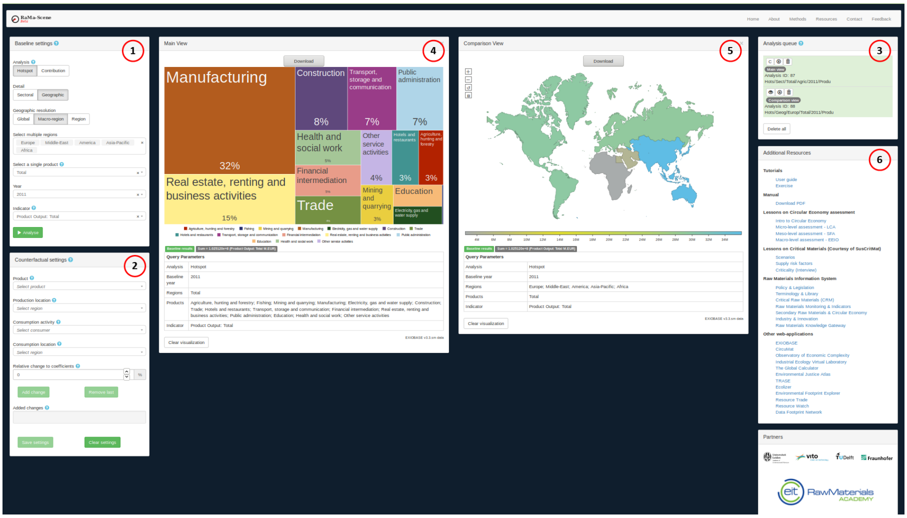

Figure 1: RaMa-Scene interface and panels

The first panel is the *Baseline settings* menu, where the user defines the type of analysis (hotspot or contribution) and the detail (sectoral or geographic) of the visualization, as well the year considered for the baseline scenario and the sectors, regions and indicator used in the visualization. The type of analysis is selected in the field *Analysis*. The visualization focus is selected in the field *Detail*, where *sectoral* leads to a *tree-map* visualization and *geographic* to a *geo-map*. The *Year*, *Region*, *Product* and *Indicator* fields are obvious. Note that depending on the detail of the visualization either one or several regions or products must be selected. Products and regions are characterized by a classification tree, such that it is possible to select items at different hierarchical levels (e.g., agriculture vs. rice or Europe vs. France). At the bottom of the panel the green button *"Analyze"* generates an analysis, which appears in the queue of panel 5, explained below.

The second panel is the *Counterfactual settings* menu, where the user defines the counterfactual scenario by editing specific parameters of the baseline scenario. Four fields allow specifying the row and column coordinates in the IO system, and a fifth field called *Relative Change to Coefficients* allows introducing the numerical value of the relative change (in percent) that the coefficient should be subjected to. The four coordinate fields are:

- *Product*, the input (or row) element to be edited;
- *Production location*, the region providing the product;
- *Consumption activity*, the sector or final demand (denoted *Y* in the pull-down menu) which uses the product defined earlier as input;
- *Consumption location* is the region in which the sector using the product is located.

At the bottom of the panel, buttons allow to manage the edits: it is possible to add new edits and to remove the last inserted. Finally, green buttons to save and clear the settings.

The third panel is the *Main View*, provides the visualization of the currently selected visualization configuration, with the details of that configuration at the bottom (under the heading *Query Parameters*), and at the top a download button.

The fourth panel is a *Comparison View* (similar to the *Main View*) provided to allow the user to compare the baseline and counterfactual scenarios.

The fifth panel is the *Analysis queue*, which contains the list of analyses that have been generated through the *Baseline settings* and *Counterfactual* *settings* menus. This queue allows the user to go back to previous assessments in the same session without having to rebuild them. To the right of each analysis there is a set of buttons: *Download*, *Delete*, *Eye*, *C* and *M*. The meaning of the first two is obvious, the *Eye* button displays the configuration in the Main View, *C* displays the configuration in the Comparison View, and *M* applies the counterfactual changes defined in the *Counterfactual settings* menu and displays the results in the Main View. The *M* button only appears after the counterfactual settings have been saved.

The sixth panel, provides additional resources that could be useful to the users. In particular, we have created a series of video tutorials for the use of the platform (i.e. user guide and exercise tutorials), educational videos to understand the concepts related to the CE and the assessment tools (Donati, Balkenende, et al., 2019) and a digital user guide (Donati, Graf, et al., 2019). In addition to these resources, through this panel users have a quick access to other web-tools and information (JRC European Commision, 2016) that could be used to improve the depth of their analyses.

4.4 USE CASES

In this section, we exemplify the use of the platform and the results from three use-cases.

4.4.1 Which country is responsible for the highest amount of material extraction due to their consumption?

For this analysis, we selected the contribution analysis at geographic detail. We choose “Domestic Extraction Used – Total” as the indicator, which is an aggregate of multiple metal and non-metal ores available in the database used RaMa-Scene. Figure 2 shows the baseline settings used and the resulting geographic visualization.

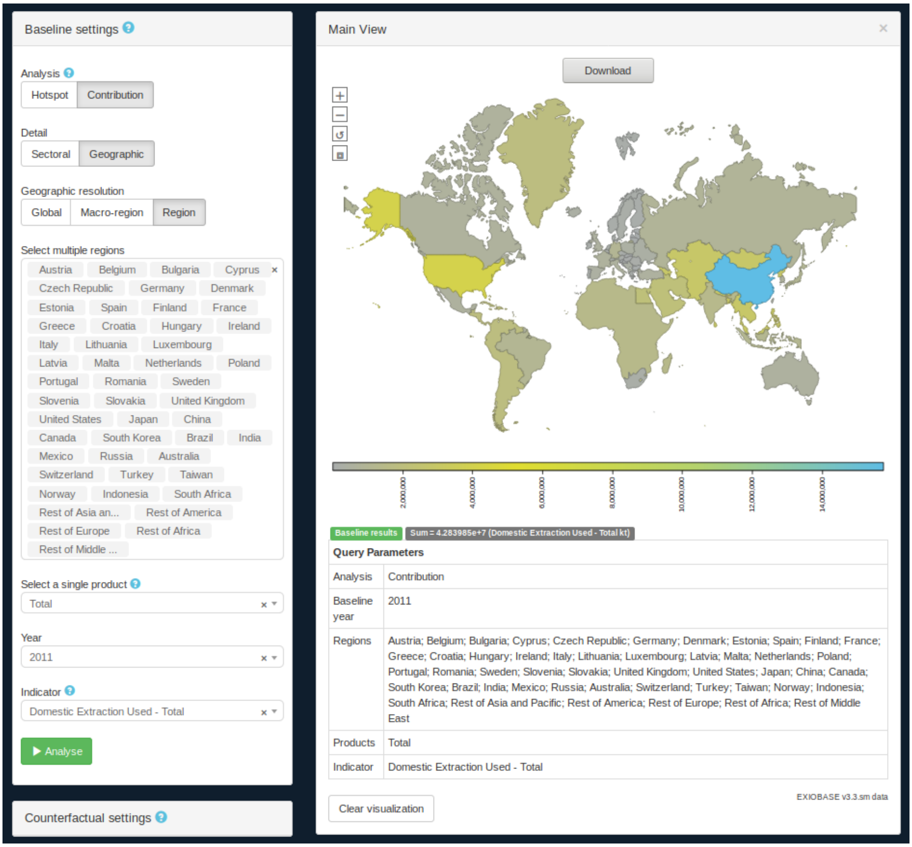

Figure 2: Regional contribution analysis of the total domestic extraction used due to regional consumption

From the visualization, we can see that China holds the largest share of extractions due to consumption. By downloading the results through the download button and calculating each country's relative share (see Annex II.a), we see that China is responsible for 37% of global Domestic Extraction Used. 'This is likely due to its share in final consumption (including investment) of both manufactured and semi-manufactured goods, whose production in turn requires a high consumption of resources. This gives an indication of how much global extractive activities are stimulated by China. China is followed by the United State of America 10%, Rest of Asia and Pacific 7% and Rest of Middle East 5%.

4.4.2 Which sub-sectors are the top CO_2-eq emitters in Italy?

In this second use-case, we investigated the sub-sectors (i.e. mid-level aggregate of product categories) with the largest GHG emissions in Italy in 2011. Figure 3 presents baseline settings used, as well as two visualizations, the hotspot analysis on the left and contribution analysis on the right. As it can be seen, the two visualizations present different results.

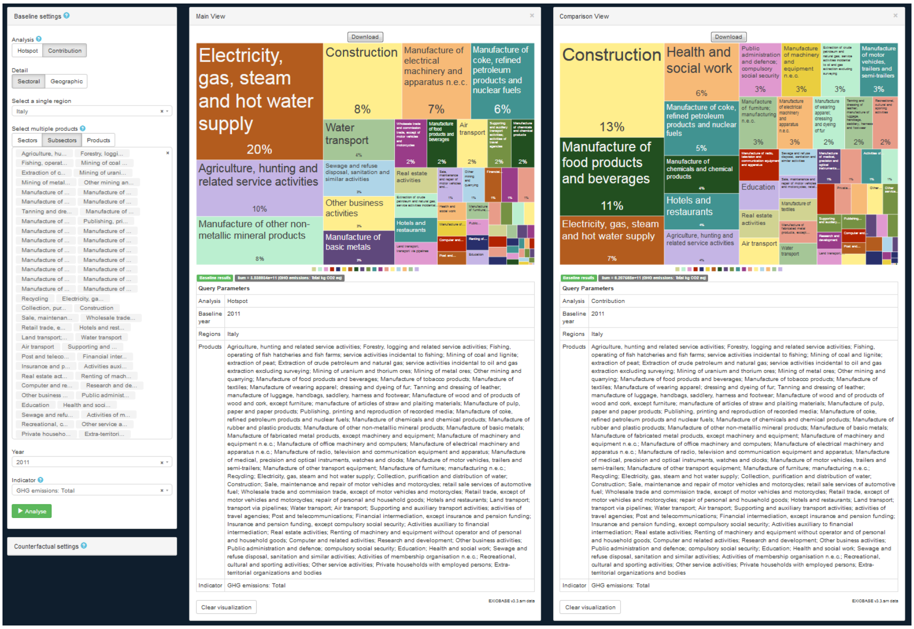

Figure 3: Sectoral hotspot (on the left) and contribution (on the right) analysis of GHG emissions in Italy

Starting from the sectoral hotspot analysis (on the left), we see that the production of electricity, gas, steam and hot water supply is responsible for 20% of the GHG emissions in Italy. This category is followed by Agriculture, hunting and related services at 10%, Manufacture of other non-metallic mineral products at 8%, Construction 8%, and Manufacture of electrical machinery and apparatus n.e.c 7% and the Manufacture of Coke, refined petroleum products and nuclear fuels at 6%. For the other product categories see annex II.b.

In the second visualization, we observe the global GHG emissions caused by consumption in Italy as opposed to the first visualization (hotspot) where we show the GHG emissions occurring due to production in Italy. The sub-sector that delivers the highest amount of emissions due its consumption in Italy, is Construction which holds a share of 13% to the total. This is followed by Manufacture of food products and beverages at 11%, Electricity, gas, steam and hot water supply at 7%, Health and social work 6%, Manufacture of coke, refined petroleum products and nuclear fuels 5%, Manufacture of chemicals and chemical products 4%. For the full analysis please see annex II.c.

4.4.3 What global effects does the increase in secondary steel content in "Electrical machinery and apparatus n.e.c." (EMA) have on total Greenhouse Gas Emissions (GHGs)?

We first analyze the total global GHG emissions due to production (fig 4) through a hotspot analysis. We select a geographic detail so we can investigate the regional location of the impacts. By doing so, we will also be able to see where the majority of GHG emissions are emitted.

By hovering on the map – or by downloading the raw results from the analysis queue-, we identify as top three largest emitters: China 27.3% (1.05e13 kg CO_2-eq); USA 13.2% (5.07e12 kg CO_2-eq); India 6.8% (2.62e12 kg CO_2-eq).

We then perform a sectoral hotspot analysis for the whole world with a focus on the product output. We look for the values concerning primary and secondary steel in the visualization or the downloaded data. This analysis shows that of the 1.816 Billion € of all steel consumed (primary and secondary), 79% is due to the production of steel from primary sources and the 21% is due to production from secondary sources. While it is currently not possible to investigate directly the consumption of steel by *"Electrical machinery and apparatus n.e.c."* (EMA), we assume that the global ratio in product output is constant in the consumption of steel for the production of all products, including EMA.

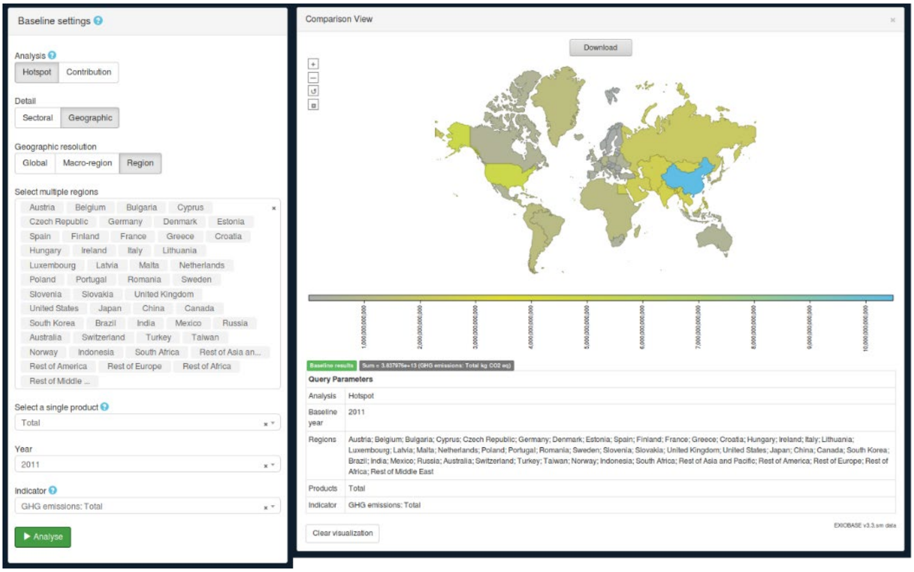

Figure 4: Baseline settings and regional distribution of total GHG emissions from production

After this analysis, we want to raise the share of secondary steel while lowering the share of primary steel, as recycled steel is less GHG emission intensive (Milford et al., 2013). We rely on (UNEP, 2013) to identify the rate of change for both secondary and primary. We see that in 2050 steel recovery rate in EMA will increase by 30% in comparison to 2007 levels. For this simplified use-case, we assume that scrap availability is directly proportional to the use of secondary materials in production.

Therefore, we increase by 30% the consumption of steel coming from secondary sources in EMA. Knowing that secondary steel amounts to 21% of the total steel consumed and assuming no price difference between primary and secondary steel, we calculate a reduction of 8% in the consumption of primary steel (table 2 and fig 4). The primary steel equivalent is calculated on the basis of global product output for the two categories. We assumed that the ratio at which the material from the two sources is used is constant across all sectors in the economy.

Table 2: Modelling scenario settings for the replacement of primary steel for secondary steel in EMA

Field	Change 1	Change 2
Product	Secondary steel for treatment, Re-processing of secondary steel into new steel	Basic iron and steel and of ferro-alloys and first products thereof
Consumed by	Electrical machinery and apparatus n.e.c.	Electrical machinery and apparatus n.e.c.
Originating from	Total (i.e. all countries and regions)	Total (i.e. all countries and regions)
Consumed where	Total (i.e. all countries and regions)	Total (i.e. all countries and regions)
Technical Change Coefficient	30%	-8%

We save the counterfactual settings and click on the modelling **M** button on the analysis queue entry for the baseline settings shown in figure 5. The results (fig 5) show that global GHG emissions reductions would amount to 2494.24 Mt CO_2-eq, -0.02% from the baseline. In particular, if we hover over China, we would see that emissions amount to 10478.89 Mt CO_2-eq, which represents a 0.02% reduction from the baseline (Annex I.f). The other regions showing important reduction of GHG emissions: Rest of Europe -0.03% (-180.38 Mt CO_2-eq) and Rest of Asia and Pacific -0.01% (-169.44 Mt CO_2-eq). However, some regions saw an increase in GHG emissions among which USA 0.01% (316.10 Mt CO_2-eq) and the majority of countries in the European continent, most EU member states, and advanced Asian economies such as South Korea, Taiwan and Japan. This is likely due to an important presence of electric arc furnaces in these countries. For additional insights, the reader can refer to annex II.e through II.f.

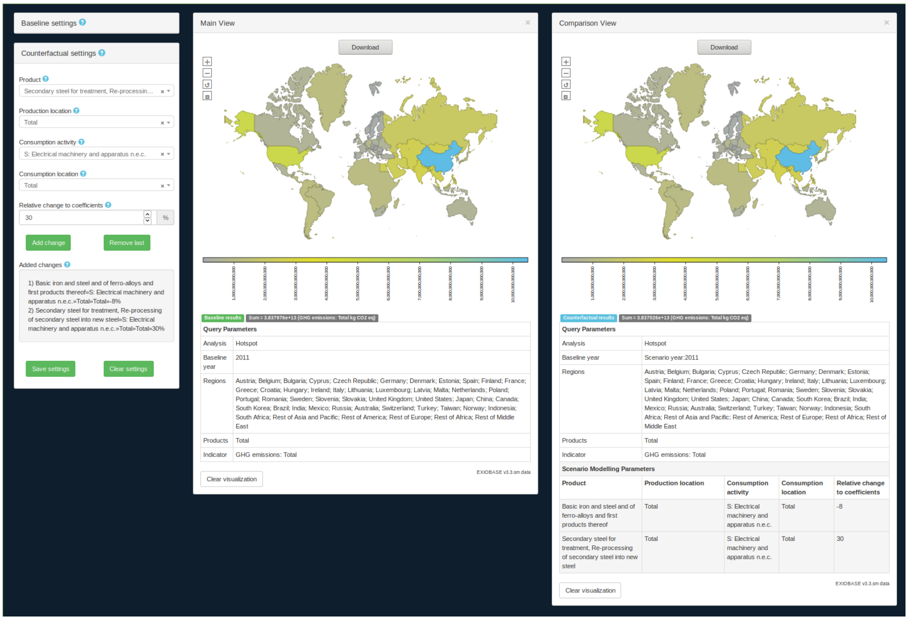

Figure 5: Total contribution of products consumption to global GHG emissions

4.5 DISCUSSION AND CONCLUSIONS

We presented a free and open-source platform, RaMa-Scene that allows for the creation of complex scenarios using the Multi-regional Environmentally-Extended Input-Output database EXIOBASE. We also make available a new version of the monetary product-by-product IO database EXIOBASE where materials produced with secondary technologies (i.e. recycling industries) are explicitly represented. The platform and database are intended as an addition to environmental impact assessment tools available for policy makers and practitioners interested in the analysis of the current structure of the global economy or the creation of CE scenarios to support decision-making.

RaMa-Scene is the first free and open-source web-application that uses a database with which users can analyze and modify the impact of CE interventions. In particular, it is the first web-platform created with the intent of allowing the creation and analysis of complex counterfactual CE scenarios. Of the analyzed software, pycirk (Donati et al.) was the only one that was also created with this intention. However, the pycirk Python package is command-line based and offers no visualizations. It is meant to be used practitioners and students comfortable with programming. On the other hand, RaMa-Scene present visualizations and functionalities approachable by different expertise levels.

RaMa-Scene's visualizations and ease of use through easy to access buttons and drop-downs was inspired by the Atlas of Economic Complexity (Hausmann et al., 2019). We combined the user-friendliness and some of the visualization of the Atlas and combined scenario modelling features similar to pycirk. However, only relative changes can be applied. The combination of these features, give users of RaMa-Scene great flexibility in the creation of any scenario of their preference. In this way, it distinguishes itself from EUREAPA (Roelich et al., 2014), where users could only choose the intensity pre-calculated scenarios. Similar to EUREAPA, RaMa-Scene employs footprint indicators but it also combines them with non-characterized extensions. This means that users can investigate variations in the extensions composing the footprints.

Other software presented more advanced features which could not be offered through RaMa-Scene. For instance, the native software REAL pyIO (Nazara et al., 2004) offers decomposition analysis and the commercial web-platform IMPLAN (IMPLAN, 2018) offers dynamic features for spending substitution. However, RaMa-Scene presents some exclusive features. Most notably, the analysis queue allowing for up to 15 analyses and multiple scenarios at the same time, and the analysis of secondary raw materials. These features give great flexibility in the investigation of Circular Economy policy options and historical trends under multiple socio-economic and environmental indicators.

Besides the comparison to previous software, we acknowledge that there are other limitations from the perspectives of methods, technical implementation and use of RaMa-Scene. From a methods perspective, RaMa-Scene uses only one transformation method from SUTs, the product-by-product industry-technology assumption. Multiple other methods and input-output configuration exist which may offer different results as the assumptions of the economic structure are different (Miller & Blair, 2009).

A few observations about the data are in order. First, the current available level of resolution of products in Input-Output data. For instance, current data does not distinguish between internal combustion engine and electric vehicles. This may prevent the modelling and assessment of some CE interventions. Secondly, in the modification of EXIOBASE as per (Donati et al.), we assumed that in each sector the consumption of secondary raw materials occurs at the same rate of primary sources. This may not be true in all cases. In the future, the database may benefit from a formal separation of materials produced with different technologies (i.e. primary and secondary technologies). Thirdly, the current database does not included final demand extensions, which may be critical for some product categories where the final-consumer use phase represents an important part of emissions (e.g. GHG emissions of personal vehicles).

From the implementation side, the Leontief inverse is computationally intensive. This is a challenge in the upscaling of the platform. One solution to this problem would be the application of formulas to avoid the re-calculation of the Leontief inverse upon changes to the technical coefficient matrix (Hager, 2005).

Currently, users cannot visualize inputs to the recipes of product category. The integration of introspective features for production recipes may prove useful to users. Additionally, while it is indeed possible to analyze different years in the database, it is not made possible to create line-graphs for time series, due to response time limitations, but users can chose two years shown simultaneously.

Lastly, the quality of a scenario is dependent on the quality of the data collection performed by the users. Therefore, the user is in complete control of the input-output coefficients and quality of scenarios. For this reason, users should make sure that their scenarios use realistic inputs keeping in mind technical and resource limitations, geographic differences and plausible substitutability. Pre-formatted scenarios such as the ones in EUREAPA (Roelich et al., 2014) and 2050 Pathway Calculator (HM Government, 2010) could facilitate users in these efforts, as well as help those interested in quick analyses.

In conclusion, the RaMa-Scene platform has multiple interesting and useful features that are currently not available on any other platforms we surveyed. At the same time, the live-tests and courses conducted in the RaMa-Scene project with practitioners, scientists and students, showed that there is still room to improve this version into a feature rich application that can be used by anybody working on environmental policy and scenario creation.

Supplementary information

Annex I and II: https://doi.org/10.5281/zenodo.7419096
Web-platform: https://www.ramascene.eu/
Software permanent repository: http://doi.org/10.5281/zenodo.3627573
Software source code: https://github.com/CMLPlatform/ramascene
Data permanent repository: http://doi.org/10.5281/zenodo.3533196

References

Aguilar-Hernandez, G. A. et al. (2018) 'Assessing circularity interventions: a review of EEIOA-based studies', *Journal of Economic Structures, 7*(1), p. 14. doi: 10.1186/s40008-018-0113-3.

Davis, C., Nikolic, I. and Dijkema, G. P. J. (2010) 'Industrial ecology 2.0', *Journal of Industrial Ecology*. doi: 10.1111/j.1530-9290.2010.00281.x.

Donati, F. et al. 'Modeling the circular economy in environmentally extended input-output tables: Methods, software and case study', *Resources, Conservation and Recycling, 152*, p. 104508. doi: 10.1016/j.resconrec.2019.104508.

Donati, F. (2019) *'CMLPlatform/pycirk: pycirk-v1.5.0'*. doi: 10.5281/zenodo.3345782.

Donati, F. et al. (2019) *RaMa-Scene Tutorials*. Available at: https://www.youtube.com/playlist?list=PLd5x9C95odZ2asmX-DEKsssBG4BBMJRPa.

Donati, F., Graf, R. and Ko, N. L. W. (2019) *RaMa-Scene User Guide*. Leiden. Available at: https://www.ramascene.eu/static/RaMaScene_platform_manual.pdf.

Donati, F. and Koning, A. de (2019) *'EXIOBASE v3.3.sm'*. doi: 10.5281/ZENODO.3533196.

GDI, C. (2008) '*Carnegie Mellon University Green Design Institute. (2008) Economic Input-Output Life Cycle Assessment (EIO-LCA) [Internet]*'. Available at: http://www.eiolca.net/cgi-bin/dft/use.pl (Accessed: 7 October 2018).

Ghosh, A. (1958) 'Input-Output Approach in an Allocation System', *Economica, 25*(97), p. 58. doi: 10.2307/2550694.

González, D. A., Gleeson, J. and McCarthy, E. (2019) 'Designing and developing a web tool to support Strategic Environmental Assessment', *Environmental Modelling and Software*. doi: 10.1016/j.envsoft.2018.10.014.

Hager, W. W. (2005) 'Updating the Inverse of a Matrix', *SIAM Review*. doi: 10.1137/1031049.

Hausmann, R. et al. (2019) The Atlas of Economic Complexity, The Atlas of Economic Complexity. doi: 10.7551/mitpress/9647.001.0001.

HM Government (2010) *'2050 Pathways Analysis'*, Analysis. doi: Ref: 10D/764.

IMPLAN (2018) *Economic Impact Analysis for Planning | IMPLAN.* Available at: http://implan.com/ (Accessed: 9 October 2018).

Jackson, R. W. and Court, C. D. (2019) *IO-Snap*. Available at: https://www.io-snap.com/ (Accessed: 19 July 2019).

Jay, S. et al. (2007) ‘Environmental impact assessment: Retrospect and prospect’, *Environmental Impact Assessment Review*. doi: 10.1016/j.eiar.2006.12.001.

JRC European Commision (2016) *Raw Material Information System.* Available at: https://rmis.jrc.ec.europa.eu/ (Accessed: 6 February 2020).

Leontief, W. (1970) ‘Environmental Repercussions and the Economic Structure: An Input-Output Approach’, *The Review of Economics and Statistics, 52*(3), pp. 262–271. doi: 10.2307/1926294.

McCarthy, A., Dellink, R. and Bibas, R. (2018) The Macroeconomics of the Circular Economy Transition: A Critical Review of Modelling Approaches, *OECD Publishing.* 130. Paris. doi: https://doi.org/10.1787/af983f9a-en.

McDougall, R. and Golub, A. (2007) *‘GTAP-E: A Revised Energy-Environmental Version of the GTAP Model’*, GTAP (Global Trade Analysys Program).

Merciai, S. and Schmidt, J. (2018) ‘Methodology for the Construction of Global Multi-Regional Hybrid Supply and Use Tables for the EXIOBASE v3 Database’, *Journal of Industrial Ecology.* doi: 10.1111/jiec.12713.

Milford, R. L. et al. (2013) ‘The roles of energy and material efficiency in meeting steel industry CO2 targets’, *Environmental Science and Technology.* doi: 10.1021/es3031424.

Miller, R. E. and Blair, P. D. (2009) *‘Input - Output Analysis: Foundations and Extensions’*, Cambridge University Press, p. 784. doi: 10.1017/CBO9780511626982.

Nazara, S. et al. (2004) *‘PyIO: input output analysis with Python’*, (October).

Roelich, K. et al. (2014) ‘Improving the policy application of footprint indicators to support Europe’s transition to a one planet economy: The development of the EUREAPA tool’, *Science of the Total Environment*. doi: 10.1016/j.scitotenv.2013.10.084.

Stadler, K. et al. (2018) ‘EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables’, *Journal of Industrial Ecology*, *22*(3), pp. 502–515. doi: 10.1111/jiec.12715.

Stadler, K. (2018) *‘Pymrio - regex aggregation of stressors’*. doi: 10.5281/ZENODO.1196307.

Stone, R. (1962) ‘Multiple Classifications in Social Accounting’, *Bulletin de l’Institut International de Statistique, XXXIX*(3), pp. 215–33.

UNEP (2013) Metal Recycling: Opportunities, Limits, Infrastructure, A Report of the Working Group on the Global Metal Flows to the International Resource Panel., United Nations Environmental Programme. doi: 978-92-807-3267-2.

Voinov, A. et al. (2016) 'Modelling with stakeholders - Next generation', Environmental Modelling and Software. doi: 10.1016/j.envsoft.2015.11.016.

Wood, R. et al. (2015) 'Global sustainability accounting-developing EXIOBASE for multi-regional footprint analysis', *Sustainability (Switzerland), 7*(1), pp. 138–163. doi: 10.3390/su7010138.

5 LCI DATA FROM COMPUTER-AIDED TECHNOLOGIES AND ARTIFICIAL INTELLIGENCE: A SYSTEMATIC REVIEW

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ABSTRACT

Industrial and ecological data currently collected on supply chains is minimal in comparison with the enormous quantity and diversity of manufactured products. Meanwhile, Computer-Aided technologies (CAx) are used daily for the design and management of products' manufacturing, life cycle. As such they can generate a wealth of information about products' life cycle. Artificial intelligence (AI) methods and infrastructure are also steadily increasing society's ability to generate data, insights and automation. In this study, we investigated the combination of CAx and AI to generate, estimate and extract data for Life Cycle Inventory (LCI) modelling. We performed a systematic review of these fields covering 1995 through May 2021 using the PRISMA method. We analyzed 131 studies concerning the use of CAx (84 articles) and AI (47 articles). From the knowledge gathered in the review, we describe possible ways of using CAx and AI to obtain LCI data for existing products and their potential alternatives. Specifically, CAx provides benefits in the generation of data for life cycle stages that require industrial processing. AI provides benefits in the combination and extraction of data from heterogeneous sources, in the estimation of flows under scenarios, and it is especially helpful in highly repetitive tasks such as the creation of several alternatives. The combination of AI and CAx for LCI provides benefits for the optimization of simulated product systems from which LCI data can be obtained, generating a vast range of alternatives, estimating lifespan and maintenance of products and components.

5.1 INTRODUCTION

Products and industries need urgent changes to mitigate further negative ecological and socio-economic effects such as anthropogenic climate change and biodiversity loss. The implementation of circular and sustainable supply chains is instrumental to this objective. In order to successfully execute and track the progress of this implementation, we need to be able to promptly assess the environmental impacts of supply chains and their alternatives. The compilation of Life Cycle Inventories (LCIs) is a fundamental practice enabling this type of assessment (Guinée, 2001). However, compiling LCIs is typically a challenging and human resource intensive activity (Zargar et al., 2022). Additionally, most supply chain data has limited availability to scientists and the public due to companies' protection of intellectual property to maintain competitive advantage (Goldstein & Newell, 2019).

In order to align the need for assessment together with human limitations, estimation of LCI data through the use of Computer-Aided Technologies (CAx) and Artificial Intelligence[2] (AI) could be an attractive option. In fact, CAx are commonly used by product designers and engineers in the creation, planning manufacturing and reverse engineering of products. Similarly, AI methods such as expert systems, data mining and machine learning, can be useful to estimate and extract and process information about manufacturing activities. For example, AI methods have shown to simplify the identification of needed processes (e.g., machining such as lathing), their parameters (e.g., tooling, operating time, and energy consumption) and sequence (e.g., cutting before lathing), or the choice of materials for manufacturing (Leo Kumar, 2017). While the use of CAx for LCIs has been previously investigated (Zargar et al., 2022), a systematic use of these technologies and full integration within the data processing pipeline of LCA practitioners and product developers still remains out of reach.

[2] In the scope of this paper, we refer to first generation AI as in Artificial Narrow Intelligence. I.e. the application of intelligent systems to solve specific tasks (Kaplan & Haenlein, 2019).

In response to these developments and needs, we present a systematic review investigating how CAx and AI can be used to obtain data for LCIs. We focus on data generation, estimation and extraction, leaving prospects of LCI data collection automation to future studies. The added value of estimating data via CAx and AI include the possibility to obtain data of the highest quality short of collecting data from manufacturers (Parvatker & Eckelman, 2019; Zargar et al., 2022). This would offer the possibility to create LCIs independently from firms (i.e. reverse engineering LCIs), thereby reducing labor intensity of the LCI phase, and expanding supply chain coverage of LCIs in databases.

These objectives are addressed by following research question and sub-questions:

How can CAx and AI methods be used to obtain data for LCIs?

- How can CAx be used to obtain data for LCIs?
- How can AI methods be used to obtain data for LCIs?
- How can the combination of CAx and AI be used to obtain data for LCIs?

The remainder of this article is organized as follows. In section 2, we provide the background information for LCI, CAx and AI. In section 3, we report the methods for the systematic review. Section 4 presents summary results, insights from the studies and how these are coupled to LCIs. Section 5 describes how the methods are combined and limitation overcome. At last, sections 6 and 7 present discussions and conclusions respectively.

5.2 Background

In this section we summarize the fundamental aspects of the various technologies investigated in our work. Each of these fields is vast, as such the provided definitions are only instrumental to understand the results of the literature review and do not have the intention of describing each field to its depth. For in-depth definitions, we refer the reader to the referenced and specialized literature on the topics.

5.2.1 Life Cycle Inventories (LCIs)

LCIs are compiled during the inventory analysis phase of a Life Cycle Assessment (LCA). In this phase, practitioners compile the inputs and outputs of a product system along the life cycle (Guinée, 2001; ISO, 2006). The inventory analysis is usually considered the most time-intensive phase of LCA as all activities involved in the product life cycle are modeled. Activities are technical systems such as a process, transport and their respective aggregates (Carlson et al., 1998; Silva, 2021). Aggregates of activities form lifecycle stages (Fig. 1), from the extraction to the end-of-life (EOL) (recycle/waste management). For example the stage of manufacturing may be composed by activities such as materials manufacture, product fabrication and packaging (EPA, 1993; Silva, 2021).

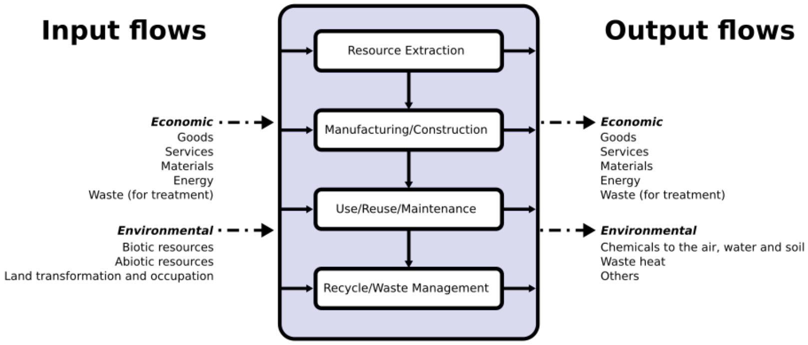

Figure 1: Lifecycle stages and flows of unit processes (adaptation from Guinée 2001; EPA 1993)

Activities, modelled as unit processes (UPs), are connected to each other by their inputs and outputs. Flows that enter and exit UPs are divided into economic and environmental flows. Economic flows are physical flows connecting UPs and concern intermediate and final products and services of positive, negative or null economic value. Environmental interventions are chemical, physical or biological anthropic interferences with the natural environment such as the extraction of resources or the emission of pollutants into nature. These quantified flows are inputs and outputs to the environment relative to the primary function(s) (i.e., functional unit) satisfied by a product system (Guinée, 2001; ISO, 2006). The wealth of information that LCIs could contain can result in heterogeneous datasets. In order to ensure a common level of information, LCA data collection is regulated by ISO (2006).

5.2.2 Computer-Aided Technologies (CAx)

CAx are a set of systems and software to support design, planning and management of products which have become indispensable to manufacturing firms and engineering education (Chryssolouris et al., 2009; Dankwort et al., 2004). They are part of a broad family of software for Product Life Management (PLM) and they compose a large ecosystem of technologies typically used in the design and planning manufacturing phase of product development. In this study, we selected a set of CAx that, to our knowledge and according to literature (Chryssolouris et al., 2009), are commonly used in engineering applications for designing products and planning their manufacturing. One additional criterion in our selection was the possibility to use CAx independently from direct interaction with firms. Such independence allows to design or reverse engineer products composition, manufacturing activities and other useful data for LCI such as economic and environmental flows. We selected the following CAx:

- ***Computer-Aided Processes Engineering (CAPE):*** The use of computer system for the design and optimization of chemical processes (Agachi, 2005);
- ***Computer-Aided Design (CAD)***: The use of computer systems for the creation, modification, analysis or optimization of a design (Elanchezhian et al., 2008);
- ***Computer-Aided Engineering (CAE):*** The use of computer software to perform simulations on physical properties of materials and goods such as structural, thermal, surface and other properties (Terzi et al., 2010). In various CAx classifications, CAE may include Computer-Aided Process Engineering and it is occasionally used to describe the totality of the computer-aided design and engineering process within a firm, however, in this study we treat these concepts separately.
- ***Computer-Aided Machining or Manufacturing (CAM):*** The use of software to plan and control manufacturing processes (Kreith & Goswami, 2004) (e.g., drills, lathes, mills or 3D printers);
- ***Computer-Aided Process Planning (CAPP):*** Tools to assist the selection, sequencing ad scheduling of manufacturing operations and their resources (ElMaraghy, 1993).

5.2.3 Artificial intelligence (AI)

AI concerns the development of *"systems that exhibit the characteristics we associate with intelligence in human behavior"* (Tecuci, 2012), such as the development of predictive models and learning complex tasks. AI is composed by 6 subfields (Russell & Norvig, 2010a): Natural Language Processing; Knowledge Representation; Automated Reasoning; Machine Learning; Computer Vision; and Robotics.

We chiefly focus on knowledge representation, automated reasoning and machine learning, and we use the following concepts to aid our study as they allow the process of obtaining and organizing knowledge useful for LCIs:

- ***Expert systems (ES)*** are knowledge-based systems that can match or exceed human experts in specific tasks, once provided with expert domain knowledge (Russell & Norvig, 2010a). These systems typically do not have learning capabilities (Negnevitsky, 2011a) and are associated with early examples of AI systems relying on Boolean logic (Russell & Norvig, 2010a). Example of expert systems may be found in decision support systems making uses of Boolean and fuzzy logic systems relying on encoded expert knowledge.
- ***Data mining (DM)*** is the process of extracting patterns from datasets, and it is an important step in the practice of knowledge discovery in databases (Fayyad et al., 1996; Han et al., 2012). While in principle data mining is not exclusive to AI, it is in practice a fundamental method in AI applications. Examples of data mining techniques are K-mean clustering, K-nearest Neighbor classification, decision trees, Bayesian Classification.
- ***Machine learning (ML)*** concerns computer systems which have the ability to learn by experience, example and analogy (Negnevitsky, 2011a). Machine learning makes great use of data mining techniques and expert systems to automatically generate rules and "*avoid the tedious and expensive processes of knowledge acquisition, validation and revision"* (Negnevitsky, 2011a). Examples of machine learning techniques are genetic algorithms, artificial neural networks and adaptive fuzzy interference systems, random forest, etc.

5.3 APPROACH TO THE LITERATURE REVIEW

This systematic review utilizes the PRISMA guidelines (Page et al., 2021) and *Web Of Knowledge Core Collection* to retrieve the relevant literature. The objective of the systematic review was to analyze how CAx and AI have been used and can be used in the compilation of LCIs. Using the definitions presented in the previous section, we created two queries: one concerning CAx and LCIs, and one for AI and LCIs. To ensure the retrieval of studies relevant to our focus but with broader labels, we included keywords for LCA and PLM in our searches.

The two searches concerned all document types in the English language from 1995 to May 2021. Any records that concerned medical research were removed before screening. We screened the articles and left out papers that incidentally contained homonyms from other fields, and those where CAx, AI and LCI were mentioned but were not employed in the methods. In the cascading phase, we analyzed the citing and cited publications in the articles that remained after screening. This step was performed to ensure the inclusion of additional literature that meets the requirements but was not in the Web of Knowledge query.

Table 1: Literature review searches

	How can CAx be used to generate data for LCI?	How can AI be used to generate data for LCI?
Keywords	Topic= ("Computer-aided" OR "PLM" OR "CAx" OR "CAD" OR "CAE" OR "CAM" OR "CAPP" OR “CAPE”) AND Topic= ("LCA" OR "LIFE CYCLE ASSESSMENT" OR "LCI" OR "LIFE CYCLE INVENTORY")	Topic = ("Artificial Intelligence" OR "Machine Learning" OR "Data mining" OR “Expert system”) AND Topic = ("LCA" OR "LIFE CYCLE ASSESSMENT" OR "LCI" OR “LIFE CYCLE INVENTORY”)
Total Results	163	109
Removed before screening	30	15
Records after screening	58	43
Total records after cascading	84	47

We classified the studies by type of CAx and AI methods used and collected data on additional techniques that may have been employed in the study. The studies were further classified by covered sectors. In order to highlight how CAx and AI can be used for LCI data, we classified the studies further by their coverage of life cycle stages and flow types (see figure 1). Additional details on the analyzed literature can be found in the supplementary information.

5.4 RESULTS

In this section, we present the results of the literature review. We start in 4.1 with an overview of the characteristics of the collected literature. We first analyze historical publication trends, and then provide a network analysis of technologies (CAx and AI) used in the literature. These are followed by an analysis of which sectors were covered, followed by a network analysis of which technologies are applied in which sector. In section 4.2 and 4.3 we discuss how CAx and AI respectively are used to estimate LCI data, and in section 4.4 we address their integration. The data and classifications used for the analyses can be found in the supplementary information to this study.

5.4.1 Overview of literature findings

The historical bibliographic analysis (Figure 2) shows a slow growth of interest in the use of CAx to gain information on the lifecycle of technologies from 1995. On the other hand, the use of AI for related technologies for lifecycle data is much more recent. While the first paper appeared in 2004, 45% of the papers were published only in 2020. Although the use of AI for LCI compilation is currently in its infancy, the publication of studies on these topics is growing rapidly.

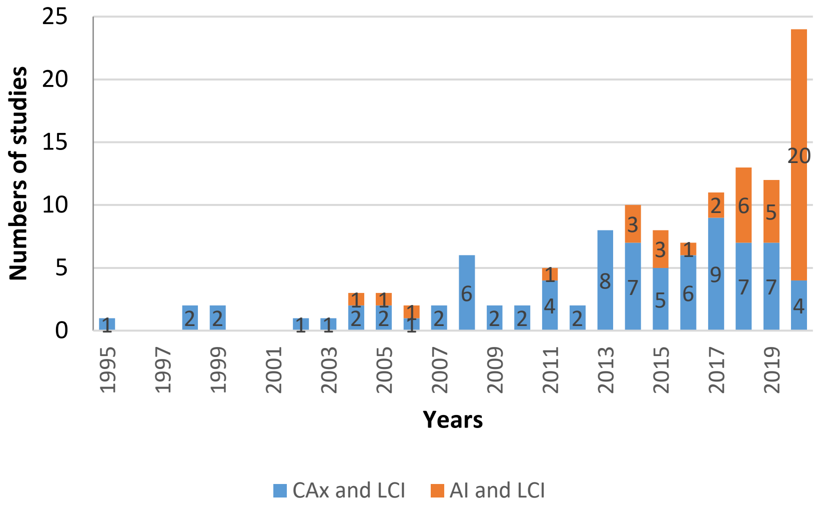

Figure 2: Published papers in the use of CAx and AI for lifecycle data in the period 1995-2020

In order to understand the attention given to each CAx and AI techniques in the context of data for LCI, we performed a network analysis (Figure 3). The circular network graph generated with the *Xnetwork* Python package show each keyword as a node, whose size is proportional to the number of articles. Each connection between nodes shows a number and is varied in thickness to indicate how frequently CAx and AI techniques were used in combination. Through this circular graph, we see that studies had a given keyword as main focus are directly connected to the main node (i.e., 131 studies (all keywords)). Combination of methods then are visible through the connections between the different keywords. For instance, one study may employ CAM as the main technology, and as a following step CAPP. The connection between these two keywords would indicate this relationship. However, the second keyword, in this case CAPP, would not have direct connection to the main node).

The network graph shows a broad use of CAD, CAPE and ML. However, they are largely disconnected with only 2 studies concerning CAPE and ML out of 45 studies concerning the two keywords. We also only found 3 articles for CAD and ML out of 80 studies for both keywords. No studies connected CAD to CAPE due to the difference in scope, as CAD focuses on the design of physical products and CAPE on the design of chemical processes. 9 studies concerned the use of ES, 6 an indirect relationship to ES through CAD. CAM, CAE, CAPP were in most cases used in combination with CAD, this is due to the fact that they rely on information provided by CAD (e.g., geometry and materials). DM, CAE, CAPP are the least employed technologies.

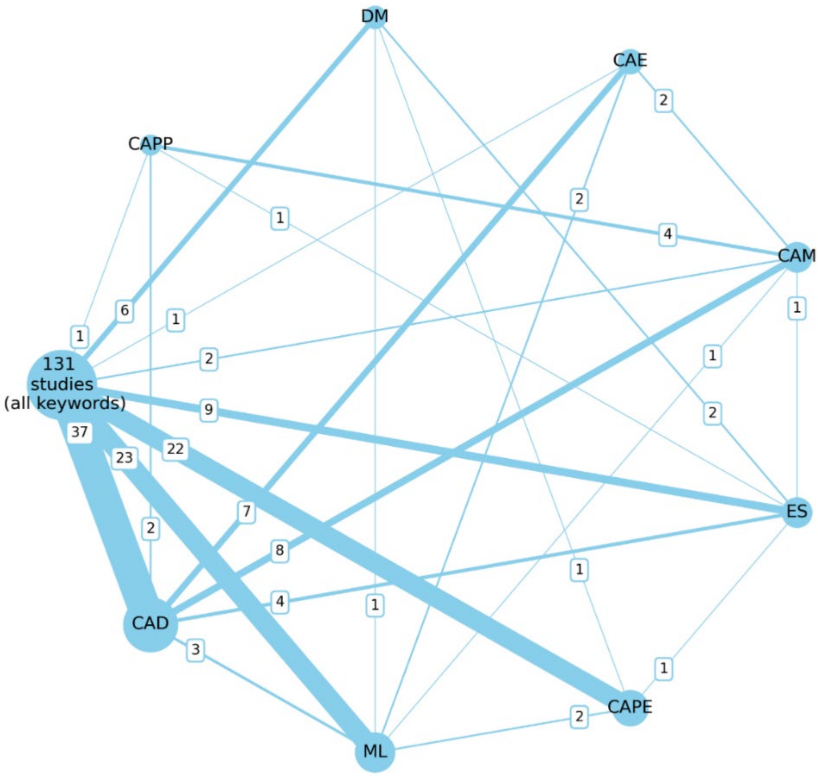

Figure 3: Technology focus in the literature and their intra-relationships. Each keyword is a node and the connections between nodes indicates combined use of the keywords. The numbers on the edges between the nodes indicate the number of studies concerning the linked CAx and AI techniques. CAD: Computer-Aided Design; CAE: Computer-Aided Engineering; CAM: Computer-Aided Machineries; CAPP: Computer-Aided Process Planning; CAPE: Computer-Aided Process Engineering; ES: Expert Systems; ML: Machine Learning; DM: Data Mining.

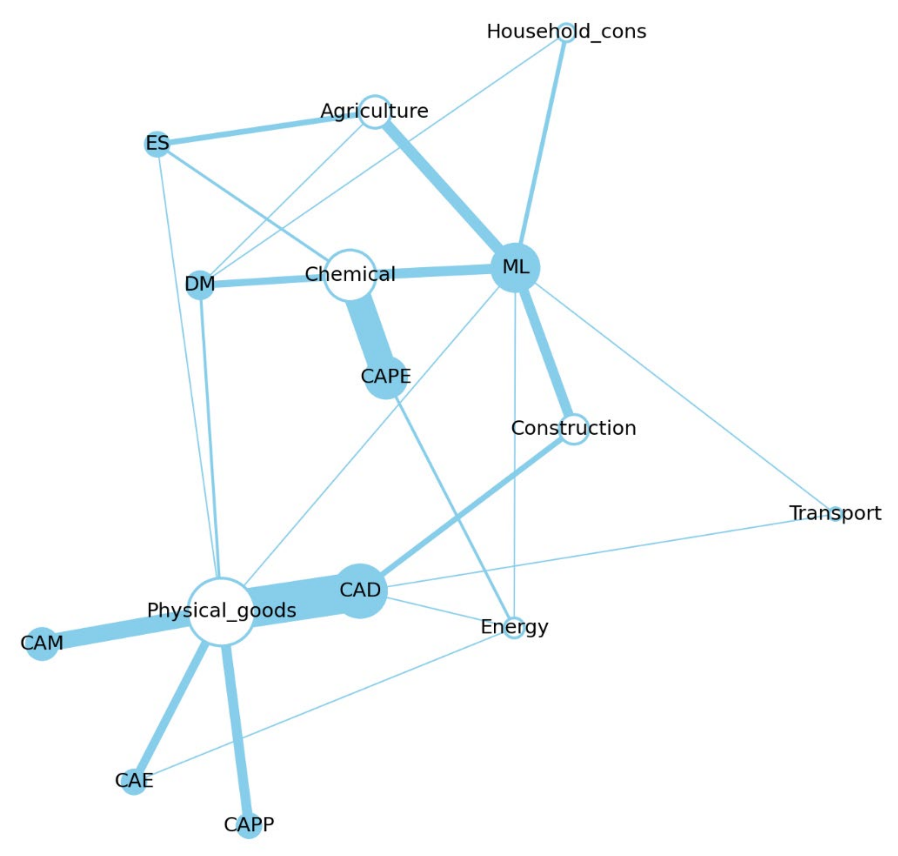

Figure 4: Sectoral focus by technology. CAD: Computer-Aided Design; CAE: Computer-Aided Engineering; CAM: Computer-Aided Machineries; CAPP: Computer-Aided Process Planning; CAPE: Computer-Aided Process Engineering; ES: Expert Systems; ML: Machine Learning; DM: Data Mining.

Figure 4 shows a network analysis of the sectors in relation to CAx and AI methods. For this analysis we used the spring layout which employs a Fruchterman-Reingold force-directed algorithm. This algorithm simulates edges as springs pulling nodes together and nodes as repelling objects. In other words, the higher the number of studies concerning the sectoral use of a CAx or AI methods the closer their nodes. From the analysis, we see that CAD, CAE, CAM and CAPP are often used in combination for LCI of physical goods (i.e., consumer and capital goods). In the construction and transportation (i.e., design, planning and assessment of transport services), the combination of ML with the use of CAD appears to be an explored avenue. However, despite the broad use of CAD for physical goods, we found little attention on how ML techniques can benefit the use of CAD for LCIs. CAPE is chiefly used in the chemical and energy sectors while ML enjoys great applications in the chemical, construction and agricultural sectors. Expert systems appear to be used mostly individually for the agricultural, and chemical sectors. Expert systems and data mining also showed some connections to CAD for physical goods. A few studies focused on general household consumption for which they employed machine learning and data mining.

Table 2: Unit process' flow types that may be estimated using the various technologies according to the literature. Each cell contains the total number of studies. Empty cells indicate no studies. A gradient from yellow (lowest number of studies) to red (highest number of studies) facilitates the identification of the least and most covered areas in data estimation for LCI.

		CAX					AI		
Stage	Flow type	CAD	CAE	CAM	CAPP	CAPE	ES	ML	DM
Resource extraction	Economic inputs	1					1	11	
	Economic outputs	1	1			1	1	11	
	Environmental inputs	1	1				3	11	
	Environmental outputs	1					3	10	
Manufacturing	Economic inputs	51	8	17	7	26	2	9	4
	Economic outputs	51	8	17	7	26	2	9	4
	Environmental inputs	27	6	10	5	26	2	9	3
	Environmental outputs	11	2	4	3	26	2	9	3
Use, Reuse,	Economic inputs	18	4	2	2			8	3
	Economic outputs	18	4	2	2			8	3
	Environmental inputs		2	1	1			5	2
	Environmental outputs							5	2
Recycling and waste	Economic inputs	11	1	1	1	2		3	2
	Economic outputs	11	1	1	1	2		3	2
	Environmental inputs				1	2		3	2
	Environmental outputs					2		3	2

Table 2 shows which flow types and life cycle stages may be generate or estimated using CAx and AI in the collected literature. The classification can be found in the supplementary information to this study. The table shows that CAx and AI have been used to estimate multiple flows and stages. The manufacturing stage has been broadly investigated both using CAx and AI. While CAx had scarce applications in the resource extraction, AI has many studies chiefly using ML with some ES applications. The distribution stage (i.e., transport and logistics from manufacturing plant to sale point) appears to not be investigated within the CAx or AI literature that we collected.

5.4.2 How CAx can be used to estimate data for LCIs

In this section we describe how CAx have been used for the estimation of each life cycle stage. The collected literature, however, revealed no CAx methods used for the estimation of LCI information for the transport stage. So this stage is discussed in the discussion section instead, together with possible ways to overcome this barrier.

Resource extraction

The analyzed literature has shown limited applications in the compilation of LCIs for the resource extraction stage. Nonetheless, in the context of agricultural products for energy or chemical production, CAPE and Computer-Aided Screening methods could be used to facilitate the identification of feedstock of agricultural origin and to be used in a specific application (Picardo et al., 2013). Once the feedstock is identified, data on the resource extraction phase could be collected or calculated. In order for this to be possible, however, the possible processes need to be modelled in CAPE software and a database needs to be provided with crops properties relevant to the modelled processes alongside information on growth conditions. However, these methods do not provide information on machineries employed for the extraction of resources.

Manufacturing

Once resources are acquired in the resource extraction stage, they are transformed into materials, parts and goods in the manufacturing stage. Most CAx applications focus on this secondary phase of the life of materials, therefore the vast majority of opportunities to estimate LCI data concerns this stage. Specifically, CAPE methods are used in the planning and design of chemical processes. CAPE achieves this by generating flowsheets containing process flow diagrams describing mass and energy balances of processes, equipment and operating conditions (Carvalho et al., 2013; Kalakul et al., 2014; Morales-Mendoza et al., 2018). This information can then be used in the simulation of plant-wide operations (Yoon et al., 2018). CAPE-generated flowsheets could be used to obtain LCI data (Romdhana et al., 2016) through the CAPE software Application Programming Interface (API) which allows to access the flowsheet of a simulated chemical production. Mass and energy balances can be used to identify all inputs and outputs, the processes and their order can be used to identify UPs, equipment tables can be used to identify equipment. Alternative processes and elementary flows, as well as uncertainties can also be identified when CAPE is linked to material property databases, knowledge based systems and optimization methods (Carvalho et al., 2013; Chen & Shonnard, 2004; Tula et al., 2017).

For goods other than chemical products, such as appliances or even buildings, the combination of CAD with CAE, CAM, CAPP and other CAx seems prominent in multiple studies (Andriankaja et al., 2017; Ben Slama et al., 2020; Tao et al., 2017, 2018; L. Zhang et al., 2019). CAD can assist in identifying economic flows linked to unit processes as the parts and materials composing the final good are known (Leibrecht, 2005). After that, CAM and CAPP can enable the retrieval of information on processes (e.g., machining), including their energy demand (Huang & Ameta, 2014b, 2014a), equipment and waste flows (Singh & Madan, 2016) as they are typically connected to manufacturing equipment databases containing specifications on operations. Specifically, CAM is used in microplanning, where processes, parameters, tooling and fluids are identified according to specific features, and CAPP is used in macroplanning, which involves the sequence of processes (Srinivasan & Sheng, 1999). The combination of multiple CAx for the design and manufacturing planning of physical goods is possible thanks to information generated by CAD software and stored within 3D CAD models, hereafter CAD models. CAD models are virtual geometric representations of goods and are stored in two types of CAD generated files (Ostad-Ahmad-Ghorabi et al., 2009):

- ***Assemblies:*** which consist of parts and subordinate assemblies (Leibrecht, 2005);

- ***Parts:*** which are made of one material and have any number of features (ibid).

Features (i.e. Feature Technology, FT) are diverse sets of information concerning for example shape, tolerances and materials (Case & Gao, 1993; Shah & Rogers, 1988). They are used to connect CAD to downstream manufacturing as they provide detailed information useful for manufacturing parts (Tao et al., 2017). The use of FT allows to automate recognition of plausible manufacturing processes and tooling and has enabled extensive investigation of the integration of CAD and other CAx such as CAE, CAM and CAPP (ibid). The reviewed studies showed that there is a long standing interest in using FT to support LCI estimation (Abad Kelly et al., 2008; Friedrich & Krasowski, 1998; Leibrecht, 2005; Otto et al., 2002). However, due to the different data structure of LCI and CAD, data transfer (i.e. interoperability) is not straightforward and prone to errors and incompleteness (Chiu & Chu, 2012; Hernandez Dalmau, 2015; Morbidoni et al., 2011). This is because LCIs focus on processes and their links to flows, while CAD models focus on the 3D representation of goods (H. Zhang et al., 2015).

This difference in ontologies across disciplines demands for common information models to allow effective transfer of data (Abad Kelly et al., 2008; Chiu & Chu, 2012; P. Yung & Wang, 2014). For this reason, Tao et al. (2017) divided FT in two main classes *Product Features* and *Operation Features*. Product features refer to the following information obtainable from CAD:

- form (e.g., name, dimensions and surface quality).
- materials[3] (e.g., name, properties, mass).
- functionality[3.]
- connectivity (e.g., connected parts, type of connection and mating relationships).

[3] n.b. not necessarily specified in CAD files

Operation features provide information through CAM and CAPP on process types, their parameters, machine and tooling specifications (e.g. resource use) and sequencing (Tao et al., 2017).

In addition to the aforementioned methods, elementary flows through unit processes can also be inventoried from CAx generated bill-of-materials (BOMs) or Building Information Models (BIM). BOMs are list of all required materials, parts and components needed to manufacture a given part or product (Cinelli et al., 2020). Building Information Modelling (BIM) offers possibilities of storing and transferring data for LCI allowing for the retrieval of buildings' parts, materials and energy performance (Mahdavi & Ries, 1998; Seo et al., 2007; P. Yung & Wang, 2014). Of particular interest, is the ability to use BIM in combination with CAD to easily generate economic inputs and outputs in construction (Seo, Tucker and Newton, 2007). However, the retrievable data from BOMs and BIMs to be used in LCI is limited (W. K. C. Yung et al., 2012). For example, while energy and auxiliary materials used in production processes may be obtained, they miss logistic information for the modelling of transportation, and in the case of BIM information on construction machineries and equipment.

Use, Reuse & Maintenance

We found no literature concerning the use of CAPE in this life cycle stage due to the fact that this lifecycle stage is typically not applicable to chemical products and substances beyond use. However, the literature showed ample opportunities to collect LCI data for physical goods and construction sectors using CAD and CAE (Chan et al., 2010; Gaha et al., 2018; Jianjun et al., 2008; Komoto & Tomiyama, 2008; Mahdavi & Ries, 1998; Umeda et al., 2012). These approaches typically involved Design-for-X (D4x) practices - where X refers to any application – and software. However, D4x applications are not common as they are typically not provided in CAx tools by default (Sy & Mascle, 2011) and often require a high level of expert knowledge to be carried out.

Some of these practices are design for disassembly, design for maintenance and design for recyclability. Maintainability and reusability (among others) can be considered life cycle features which, in addition to the product and operation features we described in the previous section, can provide information useful to compile the use, reuse and maintenance life cycle stage (Sy & Mascle, 2011). For example, knowledge on the assembly can provide information on reusability and maintenance (Rosen et al., 1996). The lifespan and score of maintainability and reuse of parts (i.e. refurbishment) can be assessed (Jianjun et al., 2008) and information on maintenance operations could be obtained through maintenance schemes generated by combining parts performance analysis in CAE. The use of CAE to assess the performance of goods though Finite Element Analysis in the use phase can provide information on the use and lifespan of a given product (Russo & Rizzi, 2014). This means that it is possible to assess uncertainty in the use stage but also in the selection of materials and processes in the manufacturing stage depending on the goods performances.

Additionally, thanks to the ability to assess performances, CAE can be of support in the identification of services related to maintenance through the generation of services oriented BOMs (Zhou et al., 2018). Service-oriented BOMs are extensive BOMs that not only contain the physical items and quantities needed to manufacture a product, but they also store service relevant information needed for maintenance, repair and overhaul throughout the product lifecycle (Zhou et al., 2018). Data concerning services can be calculated by combining users' and business/service requirement information using a Boolean approach (Xing et al., 2013). Based on these parameters, it is then possible to estimate functional, physical and economic fitness of the product (ibid). This service engineering methodologies can be replicated into CAx systems oriented toward services (i.e. Service-CAD) (Komoto & Tomiyama, 2008). Service oriented CAD tools could provide information about existing potential services that could be used for a given product (Shimomura et al., 2007) and open possibilities of Life cycle simulation approaches (Garetti et al., 2012) which could generate multiple potential alternatives. These tools could be beneficial in LCI creation and they have been shown to support Lifecycle Costing analysis (Komoto & Tomiyama, 2008; Shimomura et al., 2007). All these developments could support the creation of multiple scenarios and aiding the selection of the best alternatives using, for example, Multi-criteria Decision Support Methods (MCDSMs) in combination with CAD (Ben Slama et al., 2020).

Recycling & waste management
In section 4.2.2, we indicated that CAPE can be used to plan manufacturing activities. However, if recycling and waste management practices concern chemical processes such as in the case of processing biomass from waste sources (Romdhana et al., 2016) and reuse or conversion of CO_2 emissions (Roh et al., 2016), CAPE could be used to simulate those processes and potential alternatives. For example, various approaches such as multi-criteria decision analysis, network and graph theory and stochastic process techniques can be used to identify suitable waste and recycling treatments starting from information from the manufacturing and use stage (Fan et al., 2020).

In the life cycle of physical goods, thanks to the information on relationship among parts that is provided by assemblies and FT, it is possible to identify how a product is assembled and disassembled. Knowing this information, can be useful in understanding products' end of life and provide uncertainty values for plausible end of life treatments (Sy & Mascle, 2011). For instance, by drawing the sequence of disassembly (i.e., disassembly logic network) it is possible to map input and output flow of parts to different unit processes concerning life cycle stages after use (Jianjun et al., 2008). Graph theory in combination with CAD can also be employed to create a lifecycle model of a product in which the structure indicates connectivity and hierarchy of parts (Umeda et al., 2012). The connectivity shows relationships among parts such as how they are fixated, their signal or power transmission and motion constraints which, with the use of CAE, can support the identification of a product's fate based on its design (ibid). Once the plausible fates of a specific part or product are known, information on waste management service suppliers in a given region could be used to identify the most likely end of life treatment (Irie & Yamada, 2020). CAx could then be employed to simulate the end-of-life processes in this stage, thereby obtaining economic and environmental flows (Sy & Mascle, 2011). For example, previously developed CAx for products as complex as electronics have also helped in identify the best WEEE de-manufacturing processes according to eco-toxicity and GHG emissions levels (Chang & Lu, 2014).

At last, through the use of CAD software in construction application, BIMs and methods of construction and demolition waste assessment it is possible to identify flows concerning end of life of constructions (Mercader Moyano et al., 2019). However, this approach requires information on time of material release from construction, which is typically not readily available. However, as we have seen in previous sections, CAE could also be used to estimate the lifespan of components according to their physical performances.

5.4.3 How AI methods can be used to estimate data for LCIs

Here we describe how AI methods can be used to estimate data for LCI. The collected literature, however, revealed no AI methods used for the estimation of LCI information for the distribution stage. Therefore, distribution is presented in the discussion section instead, together with possible ways to overcome this barrier. Additionally, in this section we present only applications that did not require the combination of AI with CAx. The studies we found that describe a combination of AI methods and CAx are discussed in section 4.4 concerning the integration of AI and CAx for LCI data.

Resource extraction

The literature showed only a use of AI methods to generate LCIs for the agricultural sector. For example, in order to identify the adequate deposition of soil nutrients and other treatments in agriculture, information on specific management and operations is necessary (Renaud-Gentié et al., 2014). Additionally, farmers make choices based on a variety of factors from soil conditions to business economics, practice preferences (e.g., organic agriculture), or operations constraints that may go beyond technical aspects. This information needs to be collected from experts, literature and farming surveys and grouped according to sets of different parameters and values. Collecting and organizing this information is of course time consuming, however, if the information is already embedded within reports or scientific articles, it could be first extracted by means of text mining (e.g, Diaz-Elsayed and Zhang 2020) and organized in sets of parameters and values. These sets may be created by means of clustering techniques from data mining (e.g., K-mean clustering) to identify how frequently different choices and parameters are used in combination (Renaud-Gentié et al., 2014). This system may then also be combined with soil models and nutrients models to estimate inputs and outputs of unit processes of cropping operations

(Meza-Palacios et al., 2020). Regional data and survey (e.g., EPIC model (USDA, 2017)) can then be used to obtain regional variation of inputs and outputs (Kaab et al., 2019; Lee et al., 2020; Romeiko et al., 2020). Such applications of expert systems and data mining could present learning capabilities or be used to train an Artificial Neural Network or, in the case of fuzzy logic, to train an Adaptive Fussy Interference System (Nabavi-Pelesaraei et al., 2018). In such a case, a system would be categorized under a machine learning application. The literature has shown that such systems could be used effectively in estimating a variety of LCI data concerning future scenarios (Kaab et al., 2019; Khanali et al., 2017; Khoshnevisan et al., 2014; Khoshnevisan, Rafiee, & Mousazadeh, 2013; Khoshnevisan, Rafiee, Omid, et al., 2013; Nabavi-Pelesaraei et al., 2018). Specifically, regional climate conditions, access to water and labor may greatly influence the output of farming activities. By using these additional parameters, pre-existing LCI data and regional farming surveys (Nabavi-Pelesaraei et al., 2018), it is possible to estimate data relevant for LCIs such as energy output of biomass destined for energy generation (Kaab et al., 2019; Nabavi-Pelesaraei et al., 2018), crop yield (Khanali et al., 2017), and variety of inputs and outputs of agricultural activities (e.g., animal husbandry operations in a given region).

Manufacturing

In the context of the manufacturing stage, expert systems may be employed to transfer knowledge from one domain to the other and to identify data conversion rules (e.g., conversion of large chemical process databases to LCI data) (Meyer et al., 2021; Mittal et al., 2018a; Muñoz et al., 2018). Specifically, data that could be shared across disciplines may be labeled and organized in a different fashion than how it may be needed for the purpose of LCI modelling. In this case, the use of lineage and product ontologies have been proposed to obtain LCI data (Mittal et al., 2018a). A lineage ontology uses a family tree analogy to reconstruct all synthesis steps necessary for the production of chemicals from resource extraction to manufacturing (i.e., cradle to gate). In other words, a chemical product has own properties (e.g., the role that it plays in processes), it may be a child (i.e., the output of a reaction) and it has parent chemicals (i.e., the inputs to the reaction) defined by the reaction in which they may be involved. A process ontology is then employed to bridge this information toward LCIs to obtain elementary flows in and out of unit processes. These ontologies can help to predict products of a reaction provided that they are present in the chemical database of reference in the form of rules or algorithms (ibid). Another way to convert domain specific knowledge to LCI is through the use of machine learning applications in the field of natural language processing (Muñoz et al., 2018). Natural language processing is the field of AI that concerns the creation of systems to understand and act on text and speech in a similar way humans do. Specifically, this approach may help in the conversion of the heterogenous data that may be present in databases used by engineers and manufacturers such as facility data that may be shared with US Environmental Protection Agency through the Facility Registry Service (as shown in Mittal et al. 2018), or process recipe databases available within an enterprise (as shown in Muñoz, Capón-Garcia, and Puigjaner 2018). These databases may contain information on processes, production, materials and components and much more information that may be relevant for modelling LCIs. However, because of the diversity and large size of these databases, it is not practical to manually convert this information into LCIs. Natural language processing could be of support in this task by processing large volumes of this data, converting labels and data structures to be compatible with LCI databases (Muñoz et al., 2018).

Use, Reuse & Maintenance

The literature on this stage and the use of AI presented a vast majority of studies that focused on the combination of CAx and AI. We leave these studies for the following section concerning the integration of AI and CAx for LCI data modelling, and here we discuss the studies that did not rely on CAx software or data. The use of data mining techniques applied to regional household surveys could provide information on different regional household preferences and behaviours by creating regional household’s behavioural archetypes (Froemelt et al., 2018, 2020a). While this information cannot be used directly in the compilation of LCIs, it may be useful to estimate household habits and potential variations of product’s lifespan, reuse or maintenance. For instance, in studies outside of the scope of this research, households’ type, composition and lifestyle have shown to have an influential factor on the tendency of adopting circular economy practices (e.g., Ottelin, Cetinay, and Behrens 2020).

Recycling and Waste management

Data mining techniques could be employed to estimate regional waste types in a given sector (e.g., food packaging) provided that access to detail data on regional consumption is available. For example, if micro data from food delivery web based services is available, likely packaging types may be associated to restaurant typologies, and by following the delivery, waste accumulation may be derived (Liu et al., 2020). If data is available on regional waste collection and treatment options, it is then possible to identify the most likely end-of-life concerning a given product system, and related energy flows. In fact, once the waste flows are known, Artificial Neural Networks could be used to estimate energy consumption due to waste transport and treatment of municipal waste management alternatives in several regions, and potential energy recovery from waste (Nabavi-Pelesaraei et al., 2017). This approach could be useful when trying to quickly estimate the data concerning the end-of-life (e.g., output flows or impacts) for one or more products in different regions. These are practices that can already be performed in current LCI modelling practices, however, the employment of machine learning methods can allow for estimating these values for a large variety of regions provided..

LCI data may also be estimated starting from laboratory data. For instance, in the case of novel waste technologies for resource recovery, it may be important to estimate potential future yield. Machine learning algorithms could then be applied to laboratory data from pyrolysis where feedstock (i.e. waste flows) can be very diverse and then estimate process outputs (Cheng, Luo, et al., 2020). Specifically, by applying the Random Forest algorithm to data collected from laboratory tests, in combination with feedstock properties (e.g., content of carbon, hydrogen, nitrogen, oxygen, and ash) and processing conditions (e.g., reaction temperature and heating rate) it is possible to estimate yields and characteristics of biochar.

At last, LCI data that may have not been added to LCI database may be concealed within the written text of previous LCA scientific publications and reports. In this case, natural language processing techniques such as text mining[4] can help in the extraction of LCI data from previous publications concerning wastewater-based resource recovery systems (e.g., functional unit, water, energy and nutrient flows) (Diaz-Elsayed & Zhang, 2020). While this technique is now being discussed within the recycling and waste management stage, it could also be employed for other life cycle stages.

5.4.4 Integration: how the combination of CAx and AI methods can be used to obtain data for LCIs

The literature presented various examples that addressed the integration of CAx and AI for the purpose of obtaining data for LCIs in the following life cycle stages: 1) manufacturing, 2) use, reuse and maintenance, and 3) Recycling and waste management. In this section we do not discuss the stages individually but we rather describe how CAx and AI can be used in combination. Specifically, we saw that the integration is typically employed for the following purposes:

- Optimization of a simulated product system from which LCI data can be obtained
- Generating a vast range of alternatives (which may or may not be optimal) from which LCI can be obtained
- Estimating values concerning component's performance over their use

System optimization concerns finding the optimal parameters or organization of processes according to one or more objectives. From an LCI perspective, it concerns the identification of the optimal alternative. For example, once livestock is raised for meat products, it is lead to slaughterhouses where the animal is killed and its meat processed. CAx simulating meat process plants (e.g., Poultry Process Plants) can be used to obtain LCI data (López-Andrés et al., 2018). A Genetic Algorithm can then be employed to select optimal process parameters according to multiple

[4] To not be confused with data mining. Text mining concerns finding and extracting data from text, data mining concerns finding patterns and relationships in datasets.

objectives. Genetic Algorithms concern metaheuristic procedures from the field of evolutionary algorithms, which are inspired by the process of natural selection and they are often used to solve optimization problems. Once optimal parameters are selected, they can be used within process simulation software, thereby generating the optimal product system alternative which can then be converted into a LCI. Similar approaches have also been used to estimate optimal solar district heating installations for urban size communities (Abokersh et al., 2020).

Besides system optimization, AI and CAx can be employed together to evaluate a vast range of design options. For example, renovation and use alternatives of buildings can be identified together with their embodied and operational energy by combining the use of Artificial Neural Networks using data from CAD models and data on properties related to building components (e.g. Roof, windows, HVAC system, location etc.) (Sharif & Hammad, 2019). Regenerative design approaches (i.e., the use of AI to generate designs) could also be employed to advance the exploration of potential design options and generate LCIs. In one study (Płoszaj-Mazurek et al., 2020), this approach was to generate 300 thousand possible building design configurations according to a multitude of parameters (e.g., type of windows, façade, height, etc.). 1500 of those configurations were then randomly selected and simulated in CAD together with their energy model to estimate embodied and operational energy. This was used as the training data for a machine learning algorithm (i.e., Gradient Boosting Regressor). The trained machine learning model was then used to estimate the carbon footprint for 100 thousand of randomly generated building designs. A similar approach is not only applicable to architectural design but also to product design and process design. Additionally, it could be employed in the estimation of flows in different stages not only for footprint analysis but also in chemical process applications, i.e., CAPE (Cheng, Porter, et al., 2020; Liao et al., 2020).

At last, the combination of AI methods with CAE for the simulation of components performance can prove useful for the estimation of flows in and out of the use, reuse and maintenance stage as well as identifying when a given product or component will reach the end of life. Specifically, in order to understand the plausible failure points (e.g., abrasion of moving parts) and maintenance requirements (e.g., when lubrification may be needed) of components and goods, engineers would typically carry out laboratory tests or perform simulations such as finite element analysis or boundary element analysis, through CAE software (Kurdi et al., 2020). In other words, CAE can therefore be used to estimate wear and tear of parts and products. However, it may be challenging to integrate within CAE the knowledge obtained during experimental data from the laboratory (e.g., physically measured failure points) and to apply large volumes of variations of system parameters. In this case, machine learning methods can be used as surrogate simulation models that take into consideration simulated and empirical data over large set of possible system properties and objectives (Ibid). This information can then be used for estimation of LCI data in the use, reuse and maintenance stage of product.

5.5 DISCUSSIONS AND CONCLUSIONS

Our study revolved around the question of how CAx and AI techniques can be used to generate, estimate and extract data for LCIs. We reviewed 131 studies on the use of CAx (84) and AI (47) in the context of their potential to provide LCI data. The intent was to understand current developments of these applications and gain knowledge on how to improve data collection for the LCI modelling phase of LCA. We have found that there are many opportunities to obtain data through these approaches, however, there are also limitations that need to be addressed.

CAx provide most of their benefits in the generation of data for life cycle stages that require industrial processing of some kind, and in the sectors concerning physical goods, chemical products, construction, and energy. This is a logical result as CAx software and methods are developed specifically for the purpose of managing design and manufacturing activities. Therefore, CAx can offer relatively easy access to LCI data in the manufacturing stage, with some applications in estimating potential recycling and maintenance activities. In order to estimate data on use, reuse and other aspects of the product system that cannot be assessed easily through simulations (e.g., use, maintenance, reuse, etc.), the literature has shown various methods that rely on expert knowledge. Such expert knowledge, however, needs to be collected and encoded in expert systems which can then be used to estimate unit process data that does not concern industrial processes (e.g., use, reuse and maintenance, or the likelihood of a given part or product to undergo a given waste treatment option).

CAx applications in the resource extraction phase appeared to be scarce. AI methods have been shown of use in this stage, for the agricultural sector. However, the collected literature on CAx and AI did not show studies concerning the resource extraction for abiotic materials (e.g., metals and minerals). Also, the literature did not present any studies for the distribution stage. However, methods and software to simulate aspects of these stages exist, for instance planning software for logistics may be used to obtain data on warehouses and transport (e.g., ODL studio, openMAINT), and the field of operation research offers potential opportunities to employ AI methods and optimization methods to simulate aspects of distribution from which LCI data may be obtained. These represent important research gaps that should be further investigated.

We also showed that there are opportunities to extract data from previous studies and through the reuse of heterogenous data from different domains. The combination of expert systems, ontologies and natural language processing techniques such as text mining appear to be promising applications. However, more should be done to push the boundaries of their applications by performing a thorough search of all possible LCA publications beyond single sector studies, and in the combination of heterogeneous data from different domains not just in the chemical sector but also in agriculture and the estimation of LCIs for physical goods.

As previously stated, a great limitation of CAx in data generation and estimation for LCIs is the fundamental need for some level of expert knowledge input. While LCI data may be obtained through CAx software APIs, CAx always needs human intervention to at least create the first representation of the product (i.e., CAD model or CAPE flowsheets). Generative design approaches and computer vision methods (e.g., visual recognition and 3D reconstruction) may provide additional opportunities for LCI data and should be further investigated. Additionally, a broader investigation into the field of intelligent process engineering and process systems engineering could deliver additional insights into filling data gaps in LCIs.

At last, while CAx and AI methods separately and in combination show potential to facilitate the LCI modelling phase, the main work that lays ahead is in formalizing the integration of tools and methods from both disciplines, and in the search, development and curation of databases that can provide a solid base of data for these methods to fulfil their potential. In fact, we came across many studies in which very diverse data sources other than LCIs, had already been collected in other domains and curated or encoded in some fashion. While these methods show great promise, we cannot avoid that data collection and curation will still be needed. In other words, it is key that scientists working on LCI modelling shift their focus from current data collection and curation practices, to new ones such as investigation of heterogenous and unfamiliar sources, their combination and how to do more with them through the methods described in this study.

SUPPLEMENTARY INFORMATION

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ABBREVIATIONS

AI = Artificial Intelligence,
CAD = Computer-Aided Design
CAE = Computer-Aided Engineering
CAM = Computer-Aided Machining or Manufacturing
CAPE = Computer-Aided Process Engineering
CAPP = Computer-Aided Process Planning
CAx = Computer-Aided for x, where x stands for all possible applications
D4x = Design for x, where x stands for all possible applications
DM = Data Mining
ES = Expert System
FT = Feature Technology
ML = Machine Learning
LCA = Life Cycle Assessment
LCI = Life Cycle Inventory

REFERENCES

Abokersh, Mohamed Hany, Manel Vallès, Luisa F. Cabeza, and Dieter Boer. 2020. “A Framework for the Optimal Integration of Solar Assisted District Heating in Different Urban Sized Communities: A Robust Machine Learning Approach Incorporating Global Sensitivity Analysis.” *Applied Energy.* https://doi.org/10.1016/j.apenergy.2020.114903.

Agachi, Paul Serban. 2005. *“COMPUTER AIDED PROCESS ENGINEERING.”.*

Andriankaja, Hery, Julien Le Duigou, Christophe Danjou, and Benoît Eynard. 2017. “Sustainable Machining Approach for CAD/CAM/CNC Systems Based on a Dynamic Environmental Assessment.” Proceedings of the Institution of Mechanical Engineers, Part B: *Journal of Engineering Manufacture*. https://doi.org/10.1177/0954405416629104.

Carlson, Raul, Anne Marie Tillman, Bengt Steen, and Göran Löfgren. 1998. “LCI Data Modelling and a Database Design.” *International Journal of Life Cycle Assessment*. https://doi.org/10.1007/BF02978500.

Carvalho, Ana, Henrique A. Matos, and Rafiqul Gani. 2013. “SustainPro-A Tool for Systematic Process Analysis, Generation and Evaluation of Sustainable Design Alternatives.” *Computers and Chemical Engineering*. https://doi.org/10.1016/j.compchemeng.2012.11.007.

Case, K., and J. Gao. 1993. “Feature Technology: An Overview.” *International Journal of Computer Integrated Manufacturing,* *6*(1–2): 2–12. https://doi.org/10.1080/09511929308944549.

Chan, Clifford Chi Shing, Kai Ming Yu, and Kai Leung Yung. 2010. “Green Product Development by Using Life Cycle Assessment (LCA), Theory of Inventive of Problems Solving (TRIZ).” In Proceedings - *2010 International Conference on Manufacturing Automation*, ICMA 2010. https://doi.org/10.1109/ICMA.2010.3.

Chang, Hsiang-Tang, and Chien-Han Lu. 2014. “Simultaneous Evaluations of Material Toxicity and Ease of Disassembly during Electronics Design.” *Journal of Industrial Ecology.* https://doi.org/10.1111/jiec.12052.

Chen, Hui, and David R. Shonnard. 2004. “Systematic Framework for Environmentally Conscious Chemical Process Design: Early and Detailed Design Stages.” *Industrial and Engineering Chemistry Research.* https://doi.org/10.1021/ie0304356.

Cheng, Fangwei, Hongxi Luo, and Lisa M. Colosi. 2020. “Slow Pyrolysis as a Platform for Negative Emissions Technology: An Integration of Machine Learning Models, Life Cycle Assessment, and Economic Analysis.” *Energy Conversion and Management.* https://doi.org/10.1016/j.enconman.2020.113258.

Cheng, Fangwei, Michael D. Porter, and Lisa M. Colosi. 2020. "Is Hydrothermal Treatment Coupled with Carbon Capture and Storage an Energy-Producing Negative Emissions Technology?" *Energy Conversion and Management*. https://doi.org/10.1016/j.enconman.2019.112252.

Chiu, Ming Chuan, and Chih Hsing Chu. 2012. "Review of Sustainable Product Design from Life Cycle Perspectives." *International Journal of Precision Engineering and Manufacturing*. https://doi.org/10.1007/s12541-012-0169-1.

Chryssolouris, G., D. Mavrikios, N. Papakostas, D. Mourtzis, G. Michalos, and K. Georgoulias. 2009. "Digital Manufacturing: History, Perspectives, and Outlook." In Proceedings of the Institution of Mechanical Engineers, Part B: *Journal of Engineering Manufacture*. https://doi.org/10.1243/09544054JEM1241.

Cinelli, Matteo, Giovanna Ferraro, Antonio Iovanella, Giulia Lucci, and Massimiliano M. Schiraldi. 2020. "A Network Perspective for the Analysis of Bill of Material." Procedia CIRP, *13th CIRP Conference on Intelligent Computation in Manufacturing Engineering,* 17-19 July 2019, Gulf of Naples, Italy, 88 (January): 19–24. https://doi.org/10.1016/j.procir.2020.05.004.

Dankwort, C. Werner, Roland Weidlich, Birgit Guenther, and Joerg E. Blaurock. 2004. "Engineers' CAx Education - It's Not Only CAD." *CAD Computer Aided Design.* https://doi.org/10.1016/j.cad.2004.02.011.

Diaz-Elsayed, Nancy, and Qiong Zhang. 2020. "Extracting the Characteristics of Life Cycle Assessments via Data Mining." *MethodsX*. https://doi.org/10.1016/j.mex.2020.101004.

Elanchezhian, C., T. Selwyn Sunder, and G. Shanmuga Sundar. 2008. *Computer-Aided Manufacturing.* Second. New Delhi: LAXMI PUBLICATIONS (P) LTD.

ElMaraghy, Hoda A. 1993. "Evolution and Future Perspectives of CAPP." CIRP Annals - *Manufacturing Technology*. https://doi.org/10.1016/S0007-8506(07)62537-2.

EPA. 1993. *"United State Environmental Protection Agency. Office of Research and Development, Life Cycle Assessment: Inventory Guidelines and Principles. EPA/600/R-92/245, US."*

Fan, Yee Van, Hon Huin Chin, Jiří Jaromír Klemeš, Petar Sabev Varbanov, and Xia Liu. 2020. "Optimisation and Process Design Tools for Cleaner Production." *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2019.119181.

Fayyad, Usama, Gregory Piatetsky-Shapiro, and Padhraic Smyth. 1996. *"From Data Mining to Knowledge Discovery in Databases."* AI Magazine.

Friedrich, Jürgen, and Horst Krasowski. 1998. "Ecology-Based Product Data Model." In *SAE Technical Papers*. https://doi.org/10.4271/982227.

Froemelt, Andreas, René Buffat, and Stefanie Hellweg. 2020. “Machine Learning Based Modeling of Households: A Regionalized Bottom-up Approach to Investigate Consumption-Induced Environmental Impacts.” *Journal of Industrial Ecology*. https://doi.org/10.1111/jiec.12969.

Froemelt, Andreas, David J. Dürrenmatt, and Stefanie Hellweg. 2018. “Using Data Mining to Assess Environmental Impacts of Household Consumption Behaviors.” *Environmental Science and Technology*. https://doi.org/10.1021/acs.est.8b01452.

Gaha, Raoudha, Abdelmajid Benamara, and Bernard Yannou. 2018. “Proposition of Eco-Feature: A New CAD/PLM Data Model for an LCA Tool.” *Lecture Notes in Mechanical Engineering*, no. 207169: 763–70. https://doi.org/10.1007/978-3-319-66697-6_74.

Garetti, Marco, Paolo Rosa, and Sergio Terzi. 2012. “Life Cycle Simulation for the Design of Product-Service Systems.” *Computers in Industry.* https://doi.org/10.1016/j.compind.2012.02.007.

Goldstein, Benjamin, and Joshua P. Newell. 2019. “Why Academics Should Study the Supply Chains of Individual Corporations.” *Journal of Industrial Ecology.* https://doi.org/10.1111/jiec.12932.

Göttl, Quirin, Dominik G. Grimm, and Jakob Burger. 2021. “Automated Synthesis of Steady-State Continuous Processes Using Reinforcement Learning.” *Frontiers of Chemical Science and Engineering.* https://doi.org/10.1007/s11705-021-2055-9.

Grudziński, Jerzy Ryszard, Monika Krzywicka, and Łukasz Bolibok. 2016. “COMPUTER-AIDED ENVIRONMENTAL RISK ASSESSMENT OF POTATO CULTIVATION TECHNOLOGY USING OPENLCA SOFTWARE.” *Journal of Ecological Engineering, 17*(5): 198–202. https://doi.org/10.12911/22998993/65091.

Guinée, J. 2001. “Handbook on Life Cycle Assessment - Operational Guide to the ISO Standards.” *International Journal of Life Cycle Assessment.* https://doi.org/10.1007/BF02978784.

Han, Jiawei, Micheline Kamber, and Jian Pei. 2012. *Data Mining: Concepts and Techniques. 3rd edition*, Elsevier https://doi.org/10.1016/C2009-0-61819-5.

Hernandez Dalmau, Maria Isabel. 2015. “Eco-Design Integration into New Product Development Processes: Comparison between LCA Software and CAD-Integrated Tools.” ProQuest Dissertations and Theses, 100.

Huang, He, and Gaurav Ameta. 2014a. “A Novel Pattern for Energy Estimation Framework and Tools to Compute Energy Consumption in Product Life Cycle.” *Journal of Computing and Information Science in Engineering.* https://doi.org/10.1115/1.4025718.

———. 2014b. "Computational Energy Estimation Tools for Machining Operations during Preliminary Design." *International Journal of Sustainable Engineering.* https://doi.org/10.1080/19397038.2013.862580.

Irie, Hayate, and Tetsuo Yamada. 2020. "Decision Support Model for Economical Material Carbon Recovery and Reduction by Connecting Supplier and Disassembly Part Selections." *Journal of Advanced Mechanical Design, Systems and Manufacturing.* https://doi.org/10.1299/jamdsm.2020jamdsm0024.

ISO. 2006. "14040: Environmental Management–Life Cycle Assessment—Principles and Framework." *International Organization for Standardization.*

Jianjun, Yi, Ji Baiyang, Guan Yifeng, Dong Jinxiang, and Li Chenggang. 2008. "Research on Evaluation Methodologies of Product Life Cycle Engineering Design (LCED) and Development of Its Tools." *International Journal of Computer Integrated Manufacturing.* https://doi.org/10.1080/09511920801932486.

Kaab, Ali, Mohammad Sharifi, Hossein Mobli, Ashkan Nabavi-Pelesaraei, and Kwok wing Chau. 2019. "Combined Life Cycle Assessment and Artificial Intelligence for Prediction of Output Energy and Environmental Impacts of Sugarcane Production." *Science of the Total Environment.* https://doi.org/10.1016/j.scitotenv.2019.02.004.

Kabolizade, Mostafa, Hamid Ebadi, and Ali Mohammadzadeh. 2012. "Design and Implementation of an Algorithm for Automatic 3D Reconstruction of Building Models Using Genetic Algorithm." *International Journal of Applied Earth Observation and Geoinformation, 19*(October): 104–14. https://doi.org/10.1016/j.jag.2012.05.006.

Kalakul, Sawitree, Pomthong Malakul, Kitipat Siemanond, and Rafiqul Gani. 2014. "Integration of Life Cycle Assessment Software with Tools for Economic and Sustainability Analyses and Process Simulation for Sustainable Process Design." In *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2014.01.022.

Kaplan, Andreas, and Michael Haenlein. 2019. "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence." *Business Horizons*. Elsevier Ltd. https://doi.org/10.1016/j.bushor.2018.08.004.

Khanali, Majid, Hossein Mobli, and Homa Hosseinzadeh-Bandbafha. 2017. "Modeling of Yield and Environmental Impact Categories in Tea Processing Units Based on Artificial Neural Networks." *Environmental Science and Pollution Research.* https://doi.org/10.1007/s11356-017-0234-5.

Khoshnevisan, Benyamin, Shahin Rafiee, and Hossein Mousazadeh. 2013. "Environmental Impact Assessment of Open Field and Greenhouse Strawberry Production." *European Journal of Agronomy.* https://doi.org/10.1016/j.eja.2013.05.003.

Khoshnevisan, Benyamin, Shahin Rafiee, Mahmoud Omid, Hossein Mousazadeh, and Sean Clark. 2014. “Environmental Impact Assessment of Tomato and Cucumber Cultivation in Greenhouses Using Life Cycle Assessment and Adaptive Neuro-Fuzzy Inference System.” *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2013.09.057.

Khoshnevisan, Benyamin, Shahin Rafiee, Mahmoud Omid, Hossein Mousazadeh, and Paria Sefeedpari. 2013. “Prognostication of Environmental Indices in Potato Production Using Artificial Neural Networks.” *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2013.03.028.

Komoto, H., and T. Tomiyama. 2008. “Integration of a Service CAD and a Life Cycle Simulator.” CIRP Annals - *Manufacturing Technology*. https://doi.org/10.1016/j.cirp.2008.03.001.

Kreith, Frank, and D. Yogi Goswami. 2004. *The CRC Handbook of Mechanical Engineering*: Second Edition.

Kurdi, Abdulaziz, Nahla Alhazmi, Hatem Alhazmi, and Thamer Tabbakh. 2020. “Practice of Simulation and Life Cycle Assessment in Tribology-A Review.” *Materials.* https://doi.org/10.3390/MA13163489.

Lee, Eun Kyung, Wang Jian Zhang, Xuesong Zhang, Paul R. Adler, Shao Lin, Beth J. Feingold, Haider A. Khwaja, and Xiaobo X. Romeiko. 2020. “Projecting Life-Cycle Environmental Impacts of Corn Production in the U.S. Midwest under Future Climate Scenarios Using a Machine Learning Approach.” *Science of the Total Environment.* https://doi.org/10.1016/j.scitotenv.2020.136697.

Leibrecht, Sebastian. 2005. “Fundamental Principles for CAD-Based Ecological Assessments.” *International Journal of Life Cycle Assessment.* https://doi.org/10.1065/lca2005.08.217.

Leo Kumar, S. P. 2017. “State of The Art-Intense Review on Artificial Intelligence Systems Application in Process Planning and Manufacturing.” Engineering *Applications of Artificial Intelligence.* https://doi.org/10.1016/j.engappai.2017.08.005.

Liao, Mochen, Stephen Kelley, and Yuan Yao. 2020. “Generating Energy and Greenhouse Gas Inventory Data of Activated Carbon Production Using Machine Learning and Kinetic Based Process Simulation.” *ACS Sustainable Chemistry and Engineering.* https://doi.org/10.1021/acssuschemeng.9b06522.

Liu, Gengyuan, Feni Agostinho, Huabo Duan, Guanghan Song, Xueqi Wang, Biagio F. Giannetti, Remo Santagata, Marco Casazza, and Massimiliano Lega. 2020. “Environmental Impacts Characterization of Packaging Waste Generated by Urban Food Delivery Services. A Big-Data Analysis in Jing-Jin-Ji Region (China).” *Waste Management.* https://doi.org/10.1016/j.wasman.2020.07.028.

López-Andrés, Jhony Josué, Alberto Alfonso Aguilar-Lasserre, Luis Fernando Morales-Mendoza, Catherine Azzaro-Pantel, Jorge Raúl Pérez-Gallardo, and José Octavio Rico-Contreras. 2018. "Environmental Impact Assessment of Chicken Meat Production via an Integrated Methodology Based on LCA, Simulation and Genetic Algorithms." *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2017.10.307.

Mahdavi, A., and R. Ries. 1998. "Towards Computational Eco-Analysis of Building Designs." *Computers and Structures*. https://doi.org/10.1016/S0045-7949(97)00146-6.

Mercader Moyano, María del Pilar, Patricia Edith Camporeale, and Elías Cózar-Cózar. 2019. "Evaluación de Impacto Ambiental Mediante La Introducción de Indicadores a *Un Modelo BIM de Vivienda Social." Revista Hábitat Sustentable, 9*(2): 78–93. https://doi.org/10.22320/07190700.2019.09.02.07.

Meyer, David E., Sarah Cashman, and Anthony Gaglione. 2021. "Improving the Reliability of Chemical Manufacturing Life Cycle Inventory Constructed Using Secondary Data." *Journal of Industrial Ecology, 25*(1): 20–35. https://doi.org/10.1111/jiec.13044.

Meza-Palacios, Ramiro, Alberto A. Aguilar-Lasserre, Luis F. Morales-Mendoza, José O. Rico-Contreras, Luis H. Sánchez-Medel, and Gregorio Fernández-Lambert. 2020. "Decision Support System for NPK Fertilization: A Solution Method for Minimizing the Impact on Human Health, Climate Change, Ecosystem Quality and Resources." *Journal of Environmental Science and Health - Part A Toxic/Hazardous Substances and Environmental Engineering.* https://doi.org/10.1080/10934529.2020.1787012.

Mittal, Vinit K., Sidney C. Bailin, Michael A. Gonzalez, David E. Meyer, William M. Barrett, and Raymond L. Smith. 2018. "Toward Automated Inventory Modeling in Life Cycle Assessment: The Utility of Semantic Data Modeling to Predict Real-World Chemical Production." *ACS Sustainable Chemistry and Engineering.* https://doi.org/10.1021/acssuschemeng.7b03379.

Morales-Mendoza, Luis Fernando, Catherine Azzaro-Pantel, Jean Pierre Belaud, and Adama Ouattara. 2018. "Coupling Life Cycle Assessment with Process Simulation for Ecodesign of Chemical Processes." *Environmental Progress and Sustainable Energy.* https://doi.org/10.1002/ep.12723.

Morbidoni, Alessandro, Claudio Favi, and Michele Germani. 2011. "CAD-Integrated LCA Tool: Comparison with Dedicated LCA Software and Guidelines for the Improvement." In Glocalized Solutions for Sustainability in Manufacturing - Proceedings of the 18th *CIRP International Conference on Life Cycle Engineering.* https://doi.org/10.1007/978-3-642-19692-8-99.

Muñoz, Edrisi, Elisabet Capón-Garcia, and Luis Puigjaner. 2018. "Supervised Life-Cycle Assessment Using Automated Process Inventory Based on Process Recipes." *ACS Sustainable Chemistry and Engineering*. https://doi.org/10.1021/acssuschemeng.7b04154.

Nabavi-Pelesaraei, Ashkan, Reza Bayat, Homa Hosseinzadeh-Bandbafha, Hadi Afrasyabi, and Kwok wing Chau. 2017. "Modeling of Energy Consumption and Environmental Life Cycle Assessment for Incineration and Landfill Systems of Municipal Solid Waste Management - A Case Study in Tehran Metropolis of Iran." *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2017.01.172.

Nabavi-Pelesaraei, Ashkan, Shahin Rafiee, Seyed Saeid Mohtasebi, Homa Hosseinzadeh-Bandbafha, and Kwok wing Chau. 2018. "Integration of Artificial Intelligence Methods and Life Cycle Assessment to Predict Energy Output and Environmental Impacts of Paddy Production." *Science of the Total Environment.* https://doi.org/10.1016/j.scitotenv.2018.03.088.

Negnevitsky, Michael. 2011. Artificial Intelligence: A Guide to Intelligent Systems (3rd E-Book). Addison Wesley.

Ostad-Ahmad-Ghorabi, Hesamedin, Daniel Collado-Ruiz, and Wolfgang Wimmer. 2009. "Towards Integrating LCA into CAD." In DS 58-7: Proceedings of ICED 09, *the 17th International Conference on Engineering Design*.

Ottelin, Juudit, Hale Cetinay, and Paul Behrens. 2020. "Rebound Effects May Jeopardize the Resource Savings of Circular Consumption: Evidence from Household Material Footprints." *Environmental Research Letters, 15*(10): 104044. https://doi.org/10.1088/1748-9326/abaa78.

Otto, H.E. E., K.G. G. Mueller, and F. Kimura. 2002. "A Framework for Structured Data Retrieval in LCA Using Feature Technology." Proceedings - *2nd International Symposium on Environmentally Conscious Design and Inverse Manufacturing*, 250–55. https://doi.org/10.1109/.2001.992358.

Page, Matthew J., Joanne E. McKenzie, Patrick M. Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer, et al. 2021. "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews." *Systematic Reviews.* https://doi.org/10.1186/s13643-021-01626-4.

Parvatker, Abhijeet G., and Matthew J. Eckelman. 2019. "Comparative Evaluation of Chemical Life Cycle Inventory Generation Methods and Implications for Life Cycle Assessment Results." *ACS Sustainable Chemistry and Engineering.* https://doi.org/10.1021/acssuschemeng.8b03656.

Picardo, Marta C., José Luiz De Medeiros, Juliana Garcia M. Monteiro, Ricardo Moreira Chaloub, Mario Giordano, and Ofélia De Queiroz Fernandes Araújo. 2013. "A Methodology for Screening of Microalgae as a Decision Making Tool for Energy and Green Chemical Process Applications." *Clean Technologies and Environmental Policy.* https://doi.org/10.1007/s10098-012-0508-z.

Płoszaj-Mazurek, Mateusz, Elżbieta Ryńska, and Magdalena Grochulska-Salak. 2020. "Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design." *Energies*. https://doi.org/10.3390/en13205289.

Renaud-Gentié, Christel, Stéphane Burgos, and Marc Benoît. 2014. "Choosing the Most Representative Technical Management Routes within Diverse Management Practices: Application to Vineyards in the Loire Valley for Environmental and Quality Assessment." *European Journal of Agronomy.* https://doi.org/10.1016/j.eja.2014.03.002.

Rödger, Jan-Markus, Niki Bey, Leo Alting, and Michael Z. Hauschild. 2018. "Life Cycle Targets Applied in Highly Automated Car Body Manufacturing – Method and Algorithm." *Journal of Cleaner Production, 194*(September): 786–99. https://doi.org/10.1016/j.jclepro.2018.04.148.

Roh, Kosan, Rebecca Frauzem, Rafiqul Gani, and Jay H. Lee. 2016. "Process Systems Engineering Issues and Applications towards Reducing Carbon Dioxide Emissions through Conversion Technologies." *Chemical Engineering Research and Design.* https://doi.org/10.1016/j.cherd.2016.10.007.

Romdhana, Hedi, Catherine Bonazzi, and Martine Esteban-Decloux. 2016. "Computer-Aided Process Engineering for Environmental Efficiency: Industrial Drying of Biomass." *Drying Technology*. https://doi.org/10.1080/07373937.2015.1104348.

Romeiko, Xiaobo Xue, Eun Kyung Lee, Yetunde Sorunmu, and Xuesong Zhang. 2020. "Spatially and Temporally Explicit Life Cycle Environmental Impacts of Soybean Production in the U.S. Midwest." *Environmental Science & Technology.* https://doi.org/10.1021/acs.est.9b06874.

Rosen, David W., Bert Bras, Steven L. Hassenzahl, Patrick J. Newcomb, and Thomas Yu. 1996. "Towards Computer-Aided Configuration Design for the Life Cycle." *Journal of Intelligent Manufacturing, 7*(2): 145–60. https://doi.org/10.1007/BF00177070.

Russell, Stuart, and Peter Norvig. 2010. *Artificial Intelligence: A Modern Approach* Third Edition. Pearson. https://doi.org/10.1017/S0269888900007724.

Russo, Davide, and Caterina Rizzi. 2014. "Structural Optimization Strategies to Design Green Products." *Computers in Industry.* https://doi.org/10.1016/j.compind.2013.12.009.

Seo, Seongwon, Selwyn Tucker, and Peter Newton. 2007. “Automated Material Selection and Environmental Assessment in the Context of 3D Building Modelling.” *Journal of Green Building.* https://doi.org/10.3992/jgb.2.2.51.

Shah, J. J., and M. T. Rogers. 1988. “Expert Form Feature Modelling Shell.” *Computer-Aided Design*. https://doi.org/10.1016/0010-4485(88)90041-3.

Sharif, Seyed Amirhosain, and Amin Hammad. 2019. “Developing Surrogate ANN for Selecting Near-Optimal Building Energy Renovation Methods Considering Energy Consumption, LCC and LCA.” *Journal of Building Engineering.* https://doi.org/10.1016/j.jobe.2019.100790.

Shimomura, Yoshiki, Tomohiko Sakao, Tatsunori Hara, Tamio Arai, and Tetsuo Tomiyama. 2007. “Service Explorer - a Tool for Service Design.” In *Mechatronics for Safety, Security and Dependability in a New Era.* https://doi.org/10.1016/B978-008044963-0/50050-3.

Silva, Diogo Aparecido Lopes. 2021. “Life Cycle Assessment (LCA)—Definition of Goals and Scope.” In Life Cycle Engineering and Management of Products: Theory and Practice, edited by José Augusto de Oliveira, Diogo Aparecido Lopes Silva, Fabio Neves Puglieri, and Yovana María Barrera Saavedra, 45–69. *Cham: Springer International Publishing*. https://doi.org/10.1007/978-3-030-78044-9_3.

Singh, Prince Pal, and Jatinder Madan. 2016. “A Computer-Aided System for Sustainability Assessment for the Die-Casting Process Planning.” *International Journal of Advanced Manufacturing Technology.* https://doi.org/10.1007/s00170-013-5232-2.

Slama, Hadhami Ben, Raoudha Gaha, and Abdelmajid Benamara. 2020. “Proposal of New Eco-Manufacturing Feature Interaction-Based Methodology in CAD Phase.” *International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-019-04483-7.

Srinivasan, M., and P. Sheng. 1999. “Feature Based Process Planning in Environmentally Conscious Machining - Part 2: Macroplanning.” *Robotics and Computer-Integrated Manufacturing.* https://doi.org/10.1016/S0736-5845(99)00018-6.

Sy, Mamadou, and Christian Mascle. 2011. “Product Design Analysis Based on Life Cycle Features.” *Journal of Engineering Design.* https://doi.org/10.1080/09544820903409899.

Tao, Jing, Zhaorui Chen, Suiran Yu, and Zhifeng Liu. 2017. “Integration of Life Cycle Assessment with Computer-Aided Product Development by a Feature-Based Approach.” *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2016.12.005.

Tao, Jing, Lu Li, and Suiran Yu. 2018. "An Innovative Eco-Design Approach Based on Integration of LCA, CAD\CAE and Optimization Tools, and Its Implementation Perspectives." *Journal of Cleaner Production.* https://doi.org/10.1016/j.jclepro.2018.03.213.

Tecuci, Gheorghe. 2012. "Artificial Intelligence." *Wiley Interdisciplinary Reviews: Computational Statistics*. https://doi.org/10.1002/wics.200.

Terzi, Sergio, Abdelaziz Bouras, Debashi Dutta, Marco Garetti, and Dimitris Kiritsis. 2010. "Product Lifecycle Management - From Its History to Its New Role." *International Journal of Product Lifecycle Management, 4*(4): 360–89. https://doi.org/10.1504/IJPLM.2010.036489.

Tula, Anjan Kumar, Deenesh K. Babi, Jack Bottlaender, Mario R. Eden, and Rafiqul Gani. 2017. "A Computer-Aided Software-Tool for Sustainable Process Synthesis-Intensification." *Computers and Chemical Engineering.* https://doi.org/10.1016/j.compchemeng.2017.01.001.

Umeda, Yasushi, Shinichi Fukushige, Eisuke Kunii, and Yuki Matsuyama. 2012. "LC-CAD: A CAD System for Life Cycle Design." *CIRP Annals - Manufacturing Technology*. https://doi.org/10.1016/j.cirp.2012.03.043.

USDA. 2017. *"Environmental Policy Integrated Climate (EPIC) Model | Ag Data Commons."* 2017. https://data.nal.usda.gov/dataset/environmental-policy-integrated-climate-epic-model.

Vogel, Gabriel, Lukas Schulze Balhorn, and Artur M. Schweidtmann. 2022. "Learning from Flowsheets: A Generative Transformer Model for Autocompletion of Flowsheets." *arXiv.* https://doi.org/10.48550/arXiv.2208.00859.

Xing, K., H. F. Wang, and W. Qian. 2013. "A Sustainability-Oriented Multi-Dimensional Value Assessment Model for Product-Service Development." *International Journal of Production Research.* https://doi.org/10.1080/00207543.2013.810349.

Yoon, Seongkyu, Shaun Galbraith, Bumjoon Cha, and Huolong Liu. 2018. "Flowsheet Modeling of a Continuous Direct Compression Process." In *Computer Aided Chemical Engineering.* https://doi.org/10.1016/B978-0-444-63963-9.00005-1.

Yung, Ping, and Xiangyu Wang. 2014. "A 6D CAD Model for the Automatic Assessment of Building Sustainability." *International Journal of Advanced Robotic Systems.* https://doi.org/10.5772/58446.

Yung, Winco K.C., H. K. Chan, Danny W.C. Wong, Joey H.T. So, Albert C.K. Choi, and T. M. Yue. 2012. "Eco-Redesign of a Personal Electronic Product Subject to the Energy-Using Product Directive." *International Journal of Production Research*. https://doi.org/10.1080/00207543.2011.571941.

Zargar, Shiva, Yuan Yao, and Qingshi Tu. 2022. "A Review of Inventory Modeling Methods for Missing Data in Life Cycle Assessment." *Journal of Industrial Ecology*, *26*(1676-1689). https://doi.org/10.1111/jiec.13305.

Zhang, Heng, Bicheng Zhu, Yunpeng Li, Omer Yaman, and Utpal Roy. 2015. "Development and Utilization of a Process-Oriented Information Model for Sustainable Manufacturing." *Journal of Manufacturing Systems*. https://doi.org/10.1016/j.jmsy.2015.05.003.

Zhang, Lei, Rui Jiang, Zhi feng Jin, Hai hong Huang, Xin yu Li, and Yan jiu Zhong. 2019. "CAD-Based Identification of Product Low-Carbon Design Optimization Potential: A Case Study of Low-Carbon Design for Automotive in China*." International Journal of Advanced Manufacturing Technology.* https://doi.org/10.1007/s00170-018-2653-y.

Zhou, Chunliu, Xiaobing Liu, Fanghong Xue, Hongguang Bo, and Kai Li. 2018. "Research on Static Service BOM Transformation for Complex Products." *Advanced Engineering Informatics.* https://doi.org/10.1016/j.aei.2018.02.008.

6 THE FUTURE OF ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF INDUSTRIAL ECOLOGY

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ABSTRACT

Artificial Intelligence (AI) applications and digital technologies (DTs) are increasingly present in the daily lives of citizens, in cities and in industries. These developments generate large amounts of data and enhance analytical capabilities that could benefit the industrial ecology community and sustainability research in general. With this communication we would like to address some of the opportunities, challenges and next steps that could be undertaken by the Industrial Ecology community in this realm. This article is an adapted summary of the discussion held by experts in Industrial Ecology, AI and sustainability during the 2021 Industrial Ecology Day conference session titled *"The future of artificial intelligence in the context of industrial ecology"*. In brief, building on previous studies and communications, we advise the Industrial Ecology community to: 1) create internal committees and working groups to monitor and coordinate AI applications within and outside the community; 2) promote and ensure transdisciplinary efforts; 3) determine optimal infrastructure and governance of AI for IE to minimize undesired effects; 4) act on effective representation and on reduction of digital divides.

KEYWORDS

Industrial Ecology, Artificial Intelligence, Sustainability, Digital technologies, Interdisciplinary research, Data

6.1 INTRODUCTION

The increasing diffusion of artificial intelligence (AI) applications such as machine learning, expert systems, computer vision, along with the rapid expansion of digital technologies (DTs) for data collection, storage and consumption, are providing society with an unprecedented capacity to generate insights on how to improve the quality of life and environment (UNSGHL, 2019). These developments, often referred to as the fourth industrial revolution (Combes et al., 2018), provide opportunities to improve the sustainability of society's production and consumption system and its governance (Nishant et al., 2020).

While a commonly shared definition of AI remains in many cases evasive (Frolov et al., 2021), in this paper we define it as software employing methods and models aimed at emulating or exceeding humans' intelligence and ability to accomplish given tasks of different level of complexity (Ertel, 2017; Frolov et al., 2021; Negnevitsky, 2011b). Applications of AI span across the following fields (Russell & Norvig, 2010b): Natural Language Processing; Knowledge Representation; Automated Reasoning; Machine Learning; Computer Vision; and Robotics.

However effective AI methods may be, they rely on good quality data to provide good quality insights. As such, it is paramount to discuss the potential of AI in industrial ecology (IE) in combination with data processed to generate insights. Data can come from a variety of sources using traditional quantitative and qualitative data collection methods such as surveys, interviews, etc.; but also, from sensors spread across society and a variety of applications. In this article, we also refer to global digital infrastructure as the global network of interconnected DTs such as Information and Communication Technologies (ICT) for the purpose of collecting, storing and consuming data from a multitude of sources (e.g., statistical offices and organizations, remote sensing technologies such as satellite data, smart devices, and sensors for the Internet-Of-Things, Smart Cities and Industries, and many others).

Since its foundation, IE has provided tools and knowledge to support a sustainable management of resources and environmental impacts and investigate the unintended consequences of human activities (Ayres &

Ayres, 2002a). The increasing use of AI and the expansion of DTs present great opportunities but also challenges for the IE community. The scientific and societal role of IE could be strengthened by increasing the timeliness, details and insightfulness of policy recommendations designed to tackle the great environmental challenges of our time. For example, Luque et al. (2020) argued that industrial sensing technologies could be combined with Life Cycle Assessment (LCA) and machine learning to provide real time environmental monitoring and improvement of industrial operations. Rolnick et al. (2019) presented ways in which machine learning could be employed to tackle climate change for thirteen domains from the electricity system to education and finance.

There are however challenges in the development of a global digital infrastructure and the use of AI for sustainability. For example, Xu, Cai, and Liang (2015) indicated that while big data obtained from DTs could offer new data and opportunities for analytical techniques enabling IE to develop more realistic complex system models based on the capture of the "*temporal, spatial and demographic heterogeneity of industrial systems"*, we should be aware that *"bigger data is not always better data"*. Similarly, bigger and more complex models resulting from the use of AI may not always be preferable or better than simpler ones. In fact, they may prove difficult to understand and explain or require substantial resources (i.e., energy and materials) (Lottick et al., 2019). Additionally, they could perpetrate societal biases and unfair allocation of resources, or have economic barriers causing unequal access to information and enjoyment of its benefits through society. They could cause systemic cascading shocks due to failures of nested and decentralized AI systems, or the promotion of unstainable practices that prioritize few objectives over the overall spectrum of sustainability (Galaz et al., 2021).

The recent (2022) special issue of Data Innovation in the Journal of Industrial Ecology addresses multiple of these questions with special attention to opportunities (Majeau-Bettez et al., 2022), and similar efforts are addressed also in other disciplines under the environmental science umbrella (Hsieh, 2022; McGovern et al., 2022; Rolnick et al., 2019). The present article builds on these efforts and summarizes the seminar discussion on "The future of artificial intelligence (AI) in the context of industrial ecology (IE)" which took place on the 21st of June 2021 during the Industrial Ecology Day (ISIE, 2021). Based on this knowledge, we propose a vision for the role of the AI and DTs in the future of IE. This article contextualizes the opportunities and challenges, and it indicates next steps to be taken by the IE community.

6.2 Envisioning the role of AI in IE

The diffusion of AI can greatly benefit the IE field by strengthening its capacity of mapping flows and stocks of materials and energy across society and identifying solutions to reach society's sustainability goals. We divide the IE community work in descriptive and prescriptive, where the former concerns the analysis of current and past factors and trends of societies' economic and environmental flows and stocks; while the latter is the analysis of possible and alternative future scenarios based on this accounting and other factors.

In recent years, descriptive efforts have taken advantage of remote sensing, and geographic information systems (GIS) to reach a higher level of spatio-temporal details of material flows and stock . Froemelt, Buffat, and Hellweg (2020) used machine learning to combine remote sensing and GIS-data with household budget surveys and agent-based models to develop a spatially resolved large-scale bottom-up model that is able to derive highly-detailed environmental profiles for individual households. Techniques of text mining, mode and image recognition (e.g. google street view), and analysis of night-time lights from satellite images can allow a high-resolution capture of material types and volumes in the built-environment (Arbabi et al., 2022; Corea, 2019; Mesta et al., 2019). Additionally, the expansion of *Open & Agile Smart Cities* is providing additional information through sensing technologies (Degbelo et al., 2016; *Open & Agile Smart Cities*, n.d.). Some of these data are also available in data marketplaces such as *Fiware* (Cirillo et al., 2019) and European Union Data Portal (*Datasets - Data.Europa.Eu*, n.d.) and others may also arise. These data sources could be used with AI methods such as computer vision techniques to infer additional information about the built environmental, transport modality, emissions and biodiversity in cities (Ibrahim et al., 2020).

Direct data collection could be strengthened by the expansion of DTs in industrial operations. Better data could then be used directly to assess and monitor the environmental performance of supply chains by connecting it to LCA (Luque et al., 2020). However, this is only possible if relationships between IE practitioners and industrial actors have been established. Where such privileged relationship is missing, industrial ecologists could rely on simulation tools and support the development of digital twins. Digital twins are *"digital replications of living as well as nonliving entities"* (El Saddik, 2018) such as in digital twins of the earth system (Bauer et al., 2021), of the built environment (Ketzler et al., 2020), and industrial activities.

While data collection through DTs is of great importance, the community cannot have the expectation of being able to collect all possible data. In fact, this may not even be desirable, practical or even feasible given the material requirements of DTs and concerns of data protection. For this purpose, estimation through machine learning and data mining techniques could be useful. For example, there are opportunities to be investigated in conversion of domain specific data into data useful for Life Cycle Inventories, as shown by Mittal et al (2018) in the use of data mining to convert industrial process databases in data useful for LCI. Zhao et al (2021) show how unit process data can also be estimated using machine learning. Such developments could not only benefit LCA but also Input-Output databases in mapping activities and products as well as their environmental extensions. Some authors have also started using these approaches to estimate missing data in impact categories for Life Cycle Impact Assessment starting from diverse national databases (Cashman et al., 2016). The use of these approaches should be encouraged and supported, as they reduce dependency on data requests from industrial actors.

Such approaches in data collection and estimation, as well as model creation, could then be instrumental for prescriptive efforts in the implementation of sustainability solutions. The prescriptive efforts of IE concern the prognostication of the impacts of future policies and technologies for sustainability. For example, AI can facilitate a better comprehension of households' consumption and environmental impacts by linking diverse data sources and sub-models (physically-based, agent-based and data-driven approaches) (Froemelt et al., 2018, 2020b, 2021), which can then be combined with top-down input-output models to investigate system-wide effects of demand-side sustainability solutions (Froemelt et al., 2021). It could also provide more effective energy load levelization by combining AI with energy models, and shedding light on additional factors affecting new energy systems (Zahraee et al., 2016). It could also check the validity of recommendations and optimize them against multiple values (e.g., social and environmental performance). Furthermore, intelligent systems embedded in consumer products and services could help avoid undesired effects of novel technologies, rebound effects or problem shifting, by supporting consumers toward the adoption of sustainable lifestyles or embedding sustainable management systems within a given technology.

More generally, AI can help society in designing targeted and more timely policies that take multiple values into consideration and optimize them to reduce unintended consequences. Such a holistic viewpoint has been at the core of methodologies developed by the IE community, for example in LCA. To this end, multivariate assessment and optimization of current systems and future solutions could be instrumental to avoid political and technological interventions where mitigation of ecological issues in one part of the supply chain simply shifts problems toward other parts, negatively affecting other desired outcomes. While IE methods such as LCA, Material Flow Analysis, and Environmental Input-Output Analysis have played core roles in detecting problem shifting, the combination of IE methods with AI and DTs could achieve unparalleled spatio-temporal granularity and make results more meaningful for scientists and policy makers at different level.

The severity of many social and environmental impacts depends on time and place of emissions or resource extraction. For example, companies are rapidly expanding data collection along their supply chains thanks to embedded tracking technologies. As they assess their operations, environmental impacts and the wellbeing of workers could also be quantified. This data could then be used to support their decision support systems to reduce socio-economic and environmental risks (Alavi et al., 2021) and improve their operations. In this context, AI in combination with IE methodologies can help the business community create new sustainable business models answering the social-economic and environmental challenges of our times.

6.3 Challenges

In this study we identified three main challenges:

- Resource requirements
- Data accessibility and governance
- Explainability, interpretability and causality

6.3.1 Resource requirements

Industrial ecologists have an active lead in assessing the energy and material flows and stocks embodied in products and infrastructures, and their environmental impacts. The tremendous insight generation of DTs and the use of AI require energy and materials that could exacerbate environmental pressures. For example, AI models have known issues of high energy consumption which are also projected to growth beyond 2% of the world energy consumption (Lacoste et al., 2019; Lottick et al., 2019; Strubell et al., 2019). For this reason, tools have been developed to assess the carbon intensity of models (Schmidt et al., 2022)[5, 6] which should accompany other efficiency and typical metrics (e.g., accuracy and robustness) as a push toward yielding "*novel results without increasing computational cost, and ideally reducing it"* (i.e., Green AI) (Schwartz et al., 2019). Additionally, the resource consumption of DTs has also environmental impacts of its own, so it is important to mitigate burden shifting across environmental areas of concern (e.g., from resource depletion to climate change). In this regard, attention should be given to: 1) containing the need for large Graphical Process Unit (GPU) clusters; 2) mitigating excessive dispersion of sensing technologies for monitoring; 3) avoiding repetitive data harvesting practices. Given the long history of industrial ecologists assessing unintended consequences of policies and technology implementation (Font Vivanco & van der Voet, 2014), the community has a responsibility to hold Green AI

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[5] ML CO_2 Impacts tool: https://mlco2.github.io/impact/

[6] Python based CodeCarbon: https://codecarbon.io/; https://pypi.org/project/codecarbon/

standards together with the study of minimal expansion of digital technologies.

6.3.2 Data accessibility and governance

The issue of data governance is inherently political and concerns many aspects such as data ownership, data storage, data dissemination and the question of unequal access to the digital economy. These problems often have clear reasons. For instance, detailed information from which we can derive material and energy efficiency of processes, production volumes or product compositions, are often at the core of the competitive advantage of firms. Additionally, managing and exploiting big data has become a highly profitable business model for a very limited number of internet companies. They hold and monetize vast amounts of data while they may provide limited access by the public and scientific community.

Gathering data and maintaining big databases are labor-intensive and costly activities. This creates an inherent problem in making data open access as database curators need to be concerned with financial sustainability of their operations and data confidentiality. As a result, many of the most used datasets in the IE field, such as the Life cycle inventory database *Ecoinvent* (Frischknecht & Rebitzer, 2005) or the IEA (e.g. the IEA Energy balances), are licensed and for the most part only accessible for a fee. With the expansion in data volumes there is a risk that these business models become more common and that reliance on private services to handle and manipulate such data in the AI infrastructure increases.

This represents a barrier for an equal enjoyment of data (e.g., economic, industrial and environmental data) and AI solutions regardless of the income level of data users, and it exacerbates global inequalities in data accessibility and deployment of DTs (i.e., digital divide). Data access, quality and internet infrastructure notoriously differ across regions which risk endangering sustainability (Mehrabi et al., 2020). The digital divide will continue growing unless there are policy interventions. The use of AI for sustainability should heighten awareness of these inequalities and address them whenever possible. In various cases data accessibility and openness should be expanded, such as for geographic information and the built environment.

Industrial ecologists should investigate how public and private data may be governed to serve its objective of aiding decision making for a sustainable society. They can investigate different policy frameworks and mechanisms to ensure compliance to these frameworks (Mahanti, 2021) such that quality data is available for effective use of AI. One such mechanism could be the creation of openly accessible benchmark models and datasets for common IE analytical tasks (e.g., data estimation for LCI and EEIO, or environmental impact assessment under different climate scenarios). In a variety of other AI fields, such benchmarks (e.g., MNIST and CIFAR) have been instrumental in providing quality input data to train models, promoting transparency, comparability of models and focused progress (benchmarks.ai, 2022). The existence of such benchmarks would also be in line with the current efforts for open and shared data in the IE community (Hertwich et al., 2018).

Furthermore, in order to support data availability, the system of incentives for scientists may also need to be modified to promote timeliness, wide access and interoperability of data and software of fundamental importance to sustainability objectives. Currently, scientists may not always want to publicly disseminate their work, for example, until they are able to submit a given number of publications or to ensure co-authorship in publications using their work. However understandable these practices may be, they remain undesirable behaviors which may slow down the community's ability to provide timely and replicable analysis for sustainability.

At last, AI, DTs and annexed services can be intrusive in the private life of citizens and have profound influence on their physical, mental, and financial well-being. At the same time, AI could also induce new behaviors and help reach sustainability objectives (Froemelt et al., 2018). However, currently there is a significant risk that AI could be used to support and exacerbate unsustainable levels of consumption and production. If there is no purposeful choice of direction toward sustainability from the governance perspective, the choice will be of those with the higher resources in the market to leverage AI and DTs developments. In this regard, AI and DTs should be closely scrutinized.

6.3.3 Explainability, interpretability and causality

The way AI models are able to explain the world (i.e., explainability) and their ability to be understood by humans (i.e., interpretability) are of great importance to ensure trust in sustainability insights and effectiveness of sustainability solutions. Real-world data carries over biases to intelligent systems thereby perpetuating misconceptions, discrimination and enhancing the risks of other injustices. Improving explainability could prevent these issues by better representing the heterogeneity of complex socio-economic and ecological systems, highlighting where and how humans should intervene to correct AI models and reduce biases. Additionally, in the scope of industrial ecology, especially concerning scenarios analysis and dynamic systems, it is of fundamental importance to ensure clarity between cause and outcome. For example, in the use of multi-objective optimization of production and consumption system under different climate scenarios, we need to ensure that we can identify influential factors in such scenarios and explain the dynamics governing them. This is especially important in cases where AI is employed to enhance decision making. Recent studies such as Sgaier, Huang, and Charles (2020), present strong argument in favor of causal AI as acting on outputs from AI models that do not explain the root causes leading to ineffective, biased, poor decisions.

6.4 RECOMMENDATIONS

We have several recommendations for the IE community in moving forward in the use of Artificial Intelligence (AI) and Digital Technologies (DTs):

- Creation of internal committees and working groups for AI and DTs research. Such committees and working groups could:
    - Provide research directions, and promote standards and protocols for governance of data, models and software within and outside of IE;
    - Support knowledge transfer from and to fields that successfully embarked on interoperable data sharing and best practices in AI applications;
    - Establish and/or promote data and model benchmarks as well as good modeling practices;

    - Provide a platform for networking among researchers and establish relationships with other interest groups and institutions to promote governance of AI toward sustainability.
- Support transdisciplinary and cross-societal efforts to ensure a successful implementation and use of sustainability knowledge and solutions. In particular:
    - Computer science, data science and mathematics are at the core of the expansion of the digital technologies and developments in AI and collaborations should be actively sought out to improve our methodological and technological approaches;
    - Anthropologists, social scientists, and law experts are also indispensable in understanding the consequences of AI on the social and economic organization of society. These experts carry with them different perspectives and approaches on the complex issues of sustainability;
    - Strengthen links between citizens, research, policy, industry, and communication.
- Privilege simplicity and fair trade-off between complexity, and explainability, interpretability and causality. The community objective should not be to create models as complex as the world itself, but to provide systems that not only aid sustainability but embody it while improving insights, and quality and coherency in data and models; The community should also strive to avoid always prioritizing predictive models and also direct effort to building better causal models that help us develop a better understanding of our dynamic and complex world.
- Maintain awareness of inadvertent impacts of AI and DTs due to material and energy requirements. Determining the optimal amount of data and connectivity that are required to support decision making and sustainable solutions. While IE should embrace AI developments enthusiastically, it is paramount that we are critical of the way AI is implemented and that we try to understand what such developments entail.
- Maintain awareness of the digital divide, biases, and issues of demographic diversity and representation in data and in AI enabled decision making. The IE community should employ methods of data

collection to increase representativeness and create models that take these issues into account.

In conclusion, AI can be an important instrument to solve the greatest sustainability challenges that are currently faced by humanity. However, it should not be seen as a silver bullet but, rather, as a helpful instrument to be handled with scrutiny. The IE community has a promising and yet rapidly changing path ahead. AI and digital technologies are changing the way data is handled, services and products manufactured and consumed, and society and industries governed. IE can provide tools and insights to direct such changes toward sustainability. At the same time, these advancements also have a potential to greatly support the work performed by IE. These mutually beneficial opportunities should be nurtured and actively directed to ensure we reach our sustainability objectives.

REFERENCES

Alavi, Behrouz, Madjid Tavana, and Hassan Mina. 2021. "A Dynamic Decision Support System for Sustainable Supplier Selection in Circular Economy." *Sustainable Production and Consumption* 27 (July): 905–20. https://doi.org/10.1016/J.SPC.2021.02.015.

Arbabi, Hadi, Maud Lanau, Xinyi Li, Gregory Meyers, Menglin Dai, Martin Mayfield, and Danielle Densley Tingley. 2022. "A Scalable Data Collection, Characterization, and Accounting Framework for Urban Material Stocks." *Journal of Industrial Ecology 26* (1): 58–71. https://doi.org/10.1111/jiec.13198.

Ayres, Robert U, and Leslie Ayres. 2002. *A Handbook of Industrial Ecology*. Edward Elgar Publishing.

Bauer, Peter, Bjorn Stevens, and Wilco Hazeleger. 2021. "A Digital Twin of Earth for the Green Transition." *Nature Climate Change 2021, 1*(2): 80–83. https://doi.org/10.1038/s41558-021-00986-y.

benchmarks.ai. 2022. *"Benchmarks.AI - Directory of AI Benchmarks."* 2022. https://benchmarks.ai/.

Cashman, Sarah A., David E. Meyer, Ashley N. Edelen, Wesley W. Ingwersen, John P. Abraham, William M. Barrett, Michael A. Gonzalez, Paul M. Randall, Gerardo Ruiz-Mercado, and Raymond L. Smith. 2016. "Mining Available Data from the United States Environmental Protection Agency to Support Rapid Life Cycle Inventory Modeling of Chemical Manufacturing." *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.6b02160.

Cirillo, Flavio, Gürkan Solmaz, Everton Luís Berz, Martin Bauer, Bin Cheng, and Ernö Kovacs. 2019. "A Standard-Based Open Source IoT Platform: FIWARE." *IEEE Internet of Things Magazine, 2* (3): 12–18. https://doi.org/10.1109/IOTM.0001.1800022.

Combes, Benjamin, Celine Herweijer, Pia Ramchandani, and Jasnam Sidhu. 2018. "Harnessing Artificial Intelligence for the Earth." *World Economic Forum: Fourth Industrial Revolution for the Earth Series.*

Corea, Francesco. 2019. "AI Knowledge Map: How to Classify AI Technologies.". https://doi.org/10.1007/978-3-030-04468-8_4.

"Datasets - Data.Europa.Eu." n.d. Accessed April 19, 2022. https://data.europa.eu/data/datasets?categories=envi&page=1&locale=en.

Degbelo, Auriol, Carlos Granell, Sergio Trilles, Devanjan Bhattacharya, Sven Casteleyn, and Christian Kray. 2016. "Opening up Smart Cities: Citizen-Centric Challenges and Opportunities from GIScience." *ISPRS International Journal of Geo-Information, 5*(2): 16. https://doi.org/10.3390/ijgi5020016.

Ertel, Wolfgang. 2017. *Introduction to Artificial Intelligence* (Undergraduate Topics in Computer Science). Book.

Font Vivanco, David, and Ester van der Voet. 2014. "The Rebound Effect through Industrial Ecology's Eyes: A Review of LCA-Based Studies*." International Journal of Life Cycle Assessment.* https://doi.org/10.1007/s11367-014-0802-6.

Frischknecht, Rolf, and Gerald Rebitzer. 2005. "The Ecoinvent Database System: A Comprehensive Web-Based LCA Database." *Journal of Cleaner Production, 13*(13–14): 1337–43. https://doi.org/10.1016/j.jclepro.2005.05.002.

Froemelt, Andreas, René Buffat, and Stefanie Hellweg. 2020. "Machine Learning Based Modeling of Households: A Regionalized Bottom-up Approach to Investigate Consumption-Induced Environmental Impacts." *Journal of Industrial Ecology*. https://doi.org/10.1111/jiec.12969.

Froemelt, Andreas, David J. Dürrenmatt, and Stefanie Hellweg. 2018. "Using Data Mining to Assess Environmental Impacts of Household Consumption Behaviors." *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.8b01452.

Froemelt, Andreas, Arne Geschke, and Thomas Wiedmann. 2021. "Quantifying Carbon Flows in Switzerland: Top-down Meets Bottom-up Modelling." *Environmental Research Letters, 16*(1): 014018. https://doi.org/10.1088/1748-9326/abcdd5.

Frolov, Denys, Wojciech Radziewicz, Volodymyr Saienko, Nina Kuchuk, Mykhailo Mozhaiev, Yurii Gnusov, and Yurii Onishchenko. 2021. "Theoretical And Technological Aspects Of Intelligent Systems: Problems Of Artificial Intelligence." *International Journal of Computer Science and Network Security, 21*(5): 35–38. https://doi.org/10.22937/IJCSNS.2021.21.5.6.

Galaz, Victor, Miguel A. Centeno, Peter W. Callahan, Amar Causevic, Thayer Patterson, Irina Brass, Seth Baum, et al. 2021. "Artificial Intelligence, Systemic Risks, and Sustainability." *Technology in Society*, *67*(November): 101741. https://doi.org/10.1016/J.TECHSOC.2021.101741.

Haberl, Helmut, Dominik Wiedenhofer, Franz Schug, David Frantz, Doris Virag, Christoph Plutzar, Karin Gruhler, et al. 2021. "High-Resolution Maps of Material Stocks in Buildings and Infrastructures in Austria and Germany." *Environmental Science and Technology.* https://doi.org/10.1021/acs.est.0c05642.

Hertwich, Edgar, Niko Heeren, Brandon Kuczenski, Guillaume Majeau-Bettez, Rupert J. Myers, Stefan Pauliuk, Konstantin Stadler, and Reid Lifset. 2018. "Nullius in Verba1: Advancing Data Transparency in Industrial Ecology." *Journal of Industrial Ecology.* https://doi.org/10.1111/jiec.12738.

Hsieh, William W. 2022. “Evolution of Machine Learning in Environmental Science—A Perspective.” *Environmental Data Science, 1.* https://doi.org/10.1017/eds.2022.2.

Ibrahim, Mohamed R., James Haworth, and Tao Cheng. 2020. “Understanding Cities with Machine Eyes: A Review of Deep Computer Vision in Urban Analytics.” *Cities 96*(January): 102481. https://doi.org/10.1016/j.cities.2019.102481.

ISIE. 2021. *International Industrial Ecology Day 2021* - International Society for Industrial Ecology https://is4ie.org/events/event/international-industrial-ecology-day-2021.

Ketzler, Bernd, Vasilis Naserentin, Fabio Latino, Christopher Zangelidis, Liane Thuvander, and Anders Logg. 2020. “Digital Twins for Cities: A State of the Art Review.” *Built Environment, 46*(4): 547–73. https://doi.org/10.2148/BENV.46.4.547.

Lacoste, Alexandre, Alexandra Luccioni, Victor Schmidt, and Thomas Dandres. 2019. “Quantifying the Carbon Emissions of Machine Learning.” *ArXiv:1910.09700 [Cs]*, November. http://arxiv.org/abs/1910.09700.

Lottick, Kadan, Silvia Susai, Sorelle A. Friedler, and Jonathan P. Wilson. 2019. “Energy Usage Reports: Environmental Awareness as Part of Algorithmic Accountability.” *ArXiv:1911.08354 [Cs, Stat],* December. http://arxiv.org/abs/1911.08354.

Luque, Amalia, Ana De Las Heras, María Jesús Ávila-Gutiérrez, and Francisco Zamora-Polo. 2020. “ADAPTS: An Intelligent Sustainable Conceptual Framework for Engineering Projects.” *Sensors (Switzerland)*. https://doi.org/10.3390/s20061553.

Mahanti, Rupa. 2021. Data Governance and Compliance. Data Governance and Compliance. https://doi.org/10.1007/978-981-33-6877-4.

Majeau-Bettez, Guillaume, Jean-Marc Frayret, Anu Ramaswami, Yang Li, and Niko Heeren. 2022. “Data Innovation in Industrial Ecology.” *Journal of Industrial Ecology 26*(1): 6–11. https://doi.org/10.1111/jiec.13256.

McGovern, Amy, Imme Ebert-Uphoff, David John Gagne, and Ann Bostrom. 2022. “Why We Need to Focus on Developing Ethical, Responsible, and Trustworthy Artificial Intelligence Approaches for Environmental Science.” *Environmental Data Science, 1*. https://doi.org/10.1017/eds.2022.5.

Mehrabi, Zia, Mollie J. McDowell, Vincent Ricciardi, Christian Levers, Juan Diego Martinez, Natascha Mehrabi, Hannah Wittman, Navin Ramankutty, and Andy Jarvis. 2020. “The Global Divide in Data-Driven Farming.” *Nature Sustainability 2020 4(*2): 154–60. https://doi.org/10.1038/s41893-020-00631-0.

Mesta, Carlos, Ramzy Kahhat, and Sandra Santa-Cruz. 2019. “Geospatial Characterization of Material Stock in the Residential Sector of a Latin-American

City.” *Journal of Industrial Ecology, 23*(1): 280–91. https://doi.org/10.1111/jiec.12723.

Mittal, Vinit K., Sidney C. Bailin, Michael A. Gonzalez, David E. Meyer, William M. Barrett, and Raymond L. Smith. 2018. “Toward Automated Inventory Modeling in Life Cycle Assessment: The Utility of Semantic Data Modeling to Predict Real-World Chemical Production.” *ACS Sustainable Chemistry and Engineering*. https://doi.org/10.1021/acssuschemeng.7b03379.

Negnevitsky, Michael. 2011. *Artificial Intelligence: A Guide to Intelligent Systems (3rd E-Book)*. Addison Wesley.

Nishant, Rohit, Mike Kennedy, and Jacqueline Corbett. 2020. “Artificial Intelligence for Sustainability: Challenges, Opportunities, and a Research Agenda.” *International Journal of Information Management.* https://doi.org/10.1016/j.ijinfomgt.2020.102104.

“Open & Agile Smart Cities.” n.d. Open & Agile Smart Cities. Accessed April 19, 2022. https://oascities.org/.

Peled, Yoav, and Tomer Fishman. 2021. “Estimation and Mapping of the Material Stocks of Buildings of Europe: A Novel Nighttime Lights-Based Approach.” *Resources, Conservation and Recycling.* https://doi.org/10.1016/j.resconrec.2021.105509.

David Rolnick, Priya L. Donti, Lynn H. Kaack, Kelly Kochanski, Alexandre Lacoste, Kris Sankaran, Andrew Slavin Ross, Nikola Milojevic-Dupont, Natasha Jaques, Anna Waldman-Brown, Alexandra Sasha Luccioni, Tegan Maharaj, Evan D. Sherwin, S. Karthik Mukkavilli, Konrad P. Kording, Carla P. Gomes, Andrew Y. Ng, Demis Hassabis, John C. Platt, Felix Creutzig, Jennifer Chayes, and Yoshua Bengio. 2022. Tackling Climate Change with Machine Learning. *ACM Comput. Surv. 55*, 2, Article 42 (February 2023), 96 pages. https://doi.org/10.1145/3485128

Saddik, Abdulmotaleb El. 2018. “Digital Twins: The Convergence of Multimedia Technologies.” *IEEE Multimedia, 25*(2): 87–92. https://doi.org/10.1109/MMUL.2018.023121167.

Schmidt, Victor, Goyal-Kamal, Benoit Courty, Boris Feld, SabAmine, Franklin Zhao, Aditya Joshi, et al. 2022. *Mlco2/Codecarbon: V2.0.0*. Zenodo. https://doi.org/10.5281/zenodo.6421732.

Schwartz, Roy, Jesse Dodge, Noah A. Smith, and Oren Etzioni. 2019. “Green AI.” *ArXiv:1907.10597 [Cs, Stat]*, August. http://arxiv.org/abs/1907.10597.

Sgaier, Sema K., Vincent Huang, and Grace Charles. 2020. “The Case for Causal AI.” Stanford Social Innovation Review 18 (3): 50–55. https://doi.org/10.48558/KT81-SN73.

Strubell, Emma, Ananya Ganesh, and Andrew McCallum. 2019. “Energy and Policy Considerations for Deep Learning in NLP.” *ArXiv:1906.02243 [Cs]*, June. http://arxiv.org/abs/1906.02243.

UNSGHL. 2019. *“The Age of Digital Interdependence, Report of the UN Secretary General’s High-Level Panel on Digital Cooperation.”* Geneva: Un Secretary General.

Xu, Ming, Hua Cai, and Sai Liang. 2015. “Big Data and Industrial Ecology.*” Journal of Industrial Ecology, 19*(2): 205–10. https://doi.org/10.1111/jiec.12241.

Zahraee, S. M., M. Khalaji Assadi, and R. Saidur. 2016. “Application of Artificial Intelligence Methods for Hybrid Energy System Optimization.” *Renewable and Sustainable Energy Reviews.* https://doi.org/10.1016/j.rser.2016.08.028.

Zhao, Bu, Chenyang Shuai, Ping Hou, Shen Qu, and Ming Xu. 2021. “Estimation of Unit Process Data for Life Cycle Assessment Using a Decision Tree-Based Approach.” *Environmental Science & Technology, 55*(12): 8439–46. https://doi.org/10.1021/acs.est.0c07484.

7 DISCUSSIONS AND CONCLUSIONS

7.1 INTRODUCTION

With this thesis we aimed to investigate multiple ways to facilitate and promote the environmental, social, and economic assessment of Circular Economy (CE) interventions at the macro level. The various chapters tackled different issues related to this topic. The second chapter concerned the investigation of the environmental, social and economic impacts of final consumption of imported and exported agricultural products by the Netherlands. This study was used to understand how EEIO can be used to advise policy makers in finding hot spots for reducing environmental impacts. In the third and fourth chapters we investigated methods for replicable scenario making, and tools to facilitate access and promote the use of EEIO data to analyze circular economy interventions. In the fifth chapter, we described the use of Computer-Aided (CAx) Technologies and Artificial Intelligent methods to improve data availability for LCIs and EEIO. Increased data availability can facilitate the assessment of circular economy by allowing the modelling of interventions at a detailed level to study their macro effects. Finally, in chapter six, artificial intelligence methods and digital technologies are discussed further to show ways forward for the industrial ecology community for the development of models, systems and collection of data to the benefit of sustainability and circular economy. All these chapters helped to answer the overall research questions and sub-research questions formulated in section 1.4 of this thesis, on which we elaborate in section 7.2 below. Then section 7.3 presents limitations of this thesis and future research directions while 7.4 discusses the implications for policy makers.

7.2 CONCLUSIONS

7.2.1 Introduction

In this concluding section, we address in the next paragraphs first the sub-questions as formulated in section 1.4:

- Sub-question 1 – How can MR EEIO be used for priority setting for CE interventions?
- Sub-question 2 – How can CE strategies be modelled in MR EEIO?
- Sub-question 3 – How can we create a user-friendly interface for modelling CE strategies with MR EEIO, easily accessible for non-specialists?
- Sub-question 4 - How can we use CAx and artificial intelligence methods to increase data availability for the analysis of CE?
- Sub-question 5 - How can the IE community position itself with regards to AI and digital technologies to better support sustainability and CE assessment?

We then discuss the answer on the main research question, formulated as: How can we facilitate and promote the environmental, social and economic assessment of Circular Economy interventions at the macro level?

7.2.2 How can MR EEIO be used for priority setting for CE interventions?

Chapter 2 showed an assessment with MR EEIO of the environmental and economic performances of countries and sectors with regard to agricultural and food production. The assessment demonstrated that it was possible to identify where the highest environmental pressures take place and where the highest value added is created. Additionally, a multi-indicator analysis was performed in order to avoid biased priority settings toward a single indicator, which could lead to problem shifting in phase of policy implementation. To this end, chapter 2 provides results on multiple environmental pressures (i.e., greenhouse gas emissions, water consumption, land use, raw material extraction), and additional results for other indicators and their regional and sectoral breakdown can be found in a dashboard provided in the annex to the chapter. Besides the identification of hotspots, another aspect of priority setting concerns the assessment of

CE strategies. By modelling CE strategies in chapter 3, we showed how interventions can be prioritized to obtain the maximum mitigation of environmental pressures. Chapter 4 ties these two approaches together by providing a web-application where hotspot and footprint analyses can be performed for all products and regions in EXIOBASE for a multitude of socio-economic and environmental indicators, while also modelling complex CE scenarios. Scenarios can be compared against each other and the baseline to identify the most effective CE interventions. However, our conclusions also indicate that in many instances a mere computational approach is not sufficient and contextualization of results and value judgments (e.g., where to produce) play a key role in determining whether and how a sector or an intervention should be prioritized.

7.2.3 How can CE strategies be modelled in MR EEIO?

In the third chapter of this thesis, we investigated how CE scenarios can be implemented in MR EEIO and presented procedures that promote their replicability. The described framework had the intent to clarify terminology and structure behind modelling concepts by depicting an overview of the structure of CE strategies and their implementation in MR EEIO. Based on previous literature, we showed that taking CE as the economic paradigm to be implemented, different strategies can be applied (i.e., product life extension, resource efficiency, closing supply chain loops, residual waste management) (Aguilar-Hernandez et al., 2018a). Chapter 3 developed modelling blueprints by CE strategy, which are schemes depicting elements of MR EEIO that could be modified to simulate CE interventions. This supports building transparent and replicable scenarios. More specifically, the blueprints allow to indicate which values in the IO tables need to be modified and how (e.g., reuse of a product may result in final demand changes in terms of transactions for said product and supportive services to facilitate reuse). Such blueprints are not meant to provide a rigid application of modelling approaches but rather to indicate how the interventions may be modelled. The advantage of this approach is that the blueprints may be reused by CE analysts and serve as a first attempt to standardize how CE interventions are modelled in MR EEIO, so that studies become more comparable and replicable. This is further supported by the development of the open source software tool pycirk which facilitates organization of scenarios and modelling which can be shared in a standardized format (see Donati, 2021). It has to be noted that in chapter 3 blueprints were developed only for a number of CE interventions reflecting the product lifetime extension and resource efficiency strategies, leaving closing supply chain loops and residual waste management to future research. Closing supply chain loops was not investigated since the technical implementation is highly product specific. Modelling this strategy implies that new production recipes have to be included in the MR EEIO that have re-used components or recycled materials as inputs, and current MR EEIO tables simply lack this detail. For instance, the product categories of machinery and equipment, and electrical machineries and apparatus, are too broad to allow for a meaningful modelling of closing supply chain loops. Residual waste management could also not be investigated as the complex relationship between consumption, material stocks and waste generation is only captured by physical or hybrid IO databases with a detailed waste management sector, which currently are hardly available at the level of detail required.

7.2.4 How can we create a user-friendly interface for modelling CE strategies with MR EEIO, easily accessible for non-specialists?

CE assessment with MR EEIO could be highly facilitated and promoted if MR EEIO databases and modelling software for CE assessments were easily accessible by all potential users. For this purpose, the use of openly accessible software with standardized procedures and analysis is of fundamental importance. As indicated in in chapter 3, we developed pycirk, a Python package for the modelling of CE scenarios in MR EEIO which allows users with basic programming experience to easily access MR EEIO data and create scenarios that can be easily replicated. However, pycirk still requires a knowledge of Python or command line interface, which cannot be expected from the general public or analysts who have never had experience with coding. For this reason, and based on this experience, chapter 4 developed an online scenario web-application called RaMa-Scene (RawMaterial Scenario tool). RaMa-Scene presents a dashboard through which interactive visualizations are displayed according to the user selection, and it allows for the visualization of common analytical procedures performed with MR EEIO such as environmental footprint and hotspot analysis by product and country, or geographic region. Additionally, it provides a large variety of socio-economic and environmental indicators that can be used to assess the multidimensional aspects of the CE. Furthermore, RaMa-Scene allows users to create CE scenarios, and compare their performance against the baseline data and other scenarios. However, for the same reasons we explained in the previous section, RaMa-Scene is limited to the modelling of Product Life time extension and Resource Efficiency strategies. In order to allow for the assessment of additional CE strategies such as closing supply chain loops and residual waste management various modifications are needed, in part already discussed in section 7.2.3. First, a theoretical model for closing supply chain loop interventions should be developed and implemented as standard procedure, next to enhancing product and sector detail in IO databases to ensure a meaningful product-specific assessment. Second, hybrid, or physical waste IO data should be included in or replace the current monetary IO database to assess properly CE options related to residual waste management.

7.2.5 How can we use Computer-Aided Technologies (CAx) and Artificial Intelligence (AI) methods to increase data availability for the analysis of CE?

Chapter 3 and 4 showed current MR EEIO tables are not sufficiently detailed and lack physical data useful to calculate the implications of CE interventions that require detailed information on specific products (e.g., interventions concerning closing supply chain loops). To overcome such data gaps without excessive research time input, Chapter 5 analysed via a systematic literature review if CAx and AI methods can be used to obtain detailed Life cycle inventory (LCI) data.

CAx appear to provide most of their benefits in the of data for life cycle stages that require industrial processing (e.g, manufacturing of physical goods, chemical products, construction, and energy). This is an obvious result as CAx software and methods are most often developed specifically for the purpose of managing design and manufacturing activities. CAx can therefore offer relatively easy access to LCI data in the manufacturing stage, with some applications in estimating potential recycling and maintenance activities. This is made possible by CAx’ ability to generate volumetric and material information of process inputs and outputs, and the creation of process flow diagrams for instance chemicals.

AI methods offer possibilities of converting or extracting data from different fields (i.e., domain specific data) and applications, which can be used in LCIs. This is of great relevance when heterogeneity and volumes of used data and databases goes beyond the ability of practitioners to execute the same task manually. For instance, there is data in large chemical databases and scientific articles that is currently not used in LCI databases. Through methods for natural language processing employing data mining and expert systems, it is possible to find information and relationship in data and written text that could be used in LCIs. Machine learning methods have also shown potential to facilitate the estimation of data where diversity of parameters in the product system and/or objectives are simply not possible for practitioners to perform manually.

In short, CAx have the ability of generating data and AI methods provide the ability to perform repetitive tasks beyond practitioners' ability. Our review showed their combined use is an attractive prospect that can also support LCA scenario studies for instance enabling 1) Optimization of simulated product systems; 2) Generation of a vast range of alternatives (which may or may not be optimal); 3) Estimation of values concerning component's performance over their use (e.g., estimating the life span of a product).

7.2.6 How can the IE community position itself with regards to AI and digital technologies to better support sustainability and CE assessment?

Chapter 6 discusses potential ways forward for a stronger integration of digital technologies and AI in industrial ecology. Industrial Ecology is the science that analyses the physical economy, so any data improvement benefits for the field of industrial ecology means also better tools for the assessment of circular economy. In this chapter, we showed how there are many opportunities to be exploited in the use of AI in combination with existing data and digital technologies. However, various challenges need to be overcome related to resource requirements, data accessibility and governance, explainability, interpretability, and causality. An effective mitigation of these challenges would allow for better exploitation of technological developments in AI for the purpose of promoting sustainability objectives. In particular, the IE community should establish working groups in the IE scientific community to investigate potential research directions to improve exploitation of opportunities while addressing their challenges and potential negative consequences. Such working groups could create inventories and benchmarks for data and models useful for common IE analytical tasks, promote best practices for the sustainable use of AI intelligence from the perspective of energy and material requirements, but also to mitigate potential issues related to the increase in digital divide and general misuses of AI. Generally speaking, the IE community has a responsibility to nurture and actively direct AI developments and should more purposefully engage in these activities.

7.2.7 Answer to the main research question

The former sections now allow answering the main research question:

How can we facilitate and promote the environmental, social and economic assessment of Circular Economy interventions at the macro level?

Through the chapters of this thesis, we have presented methods and software for the assessment of circular economy interventions. The methods provided ways of standardizing procedures to enable replicability of studies and hence reuse of scenarios for CE assessment at the macro level. For this purpose, it was also important that easy to use tools such as pycirk and RaMa-Scene were created to standardize methods of analysis and enable the least experienced users to easily create scenarios and assess their environmental, social and economic impacts at the macro level. However, important data limitations still need to be overcome to allow effective analysis of CE interventions in macro level analytical tools. Currently, MR EEIO tables appear to be suitable to model the economic-social-environmental trade-offs of CE strategies such as Product Life time extension and Resource efficiency improvements. However, strategies of Closing Supply Chain Loops and Residual waste management are still challenging to model as MR EEIO tables are not sufficiently detailed or may lack information on the physical dimension of production and consumption in the economy. CE implementation will require many innovations and micro level changes throughout the economy. Such micro level changes need to be modelled to estimate their potential impacts at the macro level. For this purpose, increasing data availability is fundamental. Computer-Aided Technologies and Artificial Intelligence methods can play an important role in increasing data availability to support CE policy. However, coordination of research is required within the industrial ecology community to ensure effective exploitation of AI and mitigation of its potential negative effects. The IE community should engage in actively directing AI developments by creating working groups to investigate data and model benchmarks for common IE and CE analytical tasks in line with effective governance and ethical standards. In turn, this could benefit the community by ensuring a stable stream of data to enrich LCI and MR EEIO databases.

7.3 LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

This section presents limitations of the studies performed in this thesis and indicates future directions for research concerning software and data for CE assessment. While chapter 2 investigated how MR EEIO could be used to identify hotspots across international supply chains and highlighted the importance of presenting a multi-variate analysis to policy makers, these methods are not strictly applicable for the identification of potential areas where CE interventions may be applied. In fact, chapter 2 employed well established IO methods such as the environmental Leontief model (Leontief, 1970a), regional footprint and hotspot analyses. In other words, although the CE is a new economic paradigm, we may not always need new analytical methods to assess its potential impacts. The tools at our disposal within the industrial ecology and sustainability community may be in many cases sufficient to perform CE assessments (Walzberg et al., 2021). However, we need to think critically in what combination these tools may be used, and which indicators are most appropriate depending on the research question. Wherever possible standardized combinations of tools and indicators should be integrated into software to facilitate the work of analysts to provide robust, comparable, and replicable results to decision makers.

This is not an easy task as circular economy indicators are more than plentiful, and their implementation is uncoordinated across the community. For instance, we see that even national circularity scores are measured differently across different actors and institutions (see for example Aguilar-

Hernandez et al., (2019), Colloricchio et al., (2023) and EUROSTAT, (2022a). Saidani et al., (2019) provided a taxonomy of circular economy indicators and their potential uses from micro to macro level applications. Such efforts of classifications of indicators should be applauded and followed closely. However, a continuous increase in number of methods and indicators is to some extent unavoidable as it is also shown by the vast number of beyond-GDP indicators (Hoekstra, 2019, Chapter 4) and the multiple analytical tools that may be used for circular economy assessment (e.g., Donati et al., 2021; Lange et al., 2021; Walzberg et al., 2021). Where possible, convergence of methods and indicators, and their integration in modelling software is desirable.

Nevertheless, a consensus is unlikely to be reached and it is also reasonable to expect analysts to use a variety of analytical tools depending on the research question. For instance, the demand driven model at the base of our approaches in chapter 2 through 4 is a linear model. We know, however, that socio-economic and environmental dynamics can be complex and non-linear. The hybridization of static with dynamic models, such as the use of Agent Based Modelling (e.g., Di Domenico et al., 2022) or Computable General Equilibrium Models using MR EEIO data (e.g., Winning et al., 2017), may provide additional insights into CE that are simply out of reach for linear models such as the Leontief model. As such, future research may also investigate how methods can be combined depending on the research question, their transparent application, and their replicability. This may be achieved by promoting the development of open-source software libraries and digital fora where the communities of CE scenario modelers and software developers can meet, share knowledge, and store software and methods. One example of such community can be found in in the *opensustain.tech* initiative (Augspurger et al., 2023) which keeps an inventory of all open source software for sustainability. Such initiative could be developed even further to include inputs from analysts, as well as permanent storage and online use of developed software.

As shown in chapter 3 and 4, the presented tools (i.e., pycirk and RaMa-Scene) allow for many types of environmental, social, and economic impacts using MR EEIO databases. However, the results these software output currently lack a broader context, so we do not know to what extent CE strategies bring us within an environmentally safe and socio-economically just space, or whether the modelled CE interventions need to operate within certain physical and social boundaries. Future research should seek the integration of material constraints, and other contextual information such as planetary and social boundaries into software for CE assessment (see for example O'Neill et al. (2018) or Di Domenico et al., (2022)).

Additionally, while in chapter 3 standardized methods of scenarios construction and the sharing of modelling assumptions were suggested and we see their current use by analysts (Colloricchio et al., 2023), they are yet to become common practice and they will need promotion of standards across the scientific community. The recent developments is ISO standards for measuring and assessing circularity (ISO, 2023) may represent a great opportunity in this regard, provided that they are also expanded to include guidance for the construction of CE scenarios. Such standards could then be integrated into software tools for CE assessment, thereby improving replicability and comparability of studies, and transparency of assumptions. Therefore, future research may also investigate effective ways of sharing data for scenarios construction, and the development of centralized systems to collect scenario data so that modelers can more easily access fundamental data for their analyses. For example, Creutzig et al., (2022) have conducted an in-depth review where they have collected, among others, data for CE scenarios. However, this is an annex to a scientific study, while the community of CE modelers could benefit from a web-based fora where the data could be more easily searched, reused, and expanded through time as new CE studies become available.

An important limitation found in the assessment of CE scenarios was the use of monetary MR EEIO data. In the studies performed in this thesis, there was conscious choice to use monetary data. This choice was driven by the desire to facilitate access to environmental data most commonly used by practitioners and data that is frequently curated. In fact, hybrid MR EEIO data containing physical information about the structure of the economy is uncommonly used by practitioners and analysts partly due to the lack of consistent curation by most National Statistical Offices and supranational organizations (Wiebe et al., 2018). However, CE interventions have an important physical component that is difficult to capture through monetary data. As a result, CE strategies such as Residual Waste Management and Closing Supply Chain Loops could not be modelled. Future research should integrate hybrid MR EEIO data into software tools to model circular economy scenarios, and additional efforts are needed in the promotion, expansion, and use of Hybrid MR EEIO by analysts and statical offices.

Through the modelling of CE scenarios, it also became clear that CE strategies are composed by micro-level changes across supply chains (see chapter 3). However, MR EEIO data only presents large aggregates of product categories. For example, it is often not possible to distinguish between subparts of a manufactured product (e.g., car, engine, wheels, etc). This is a big limitation in the modelling of CE interventions such as remanufacturing and repair. For this reason, chapter 5 and 6 explored potential opportunities to increase data availability on production systems. While we investigated CAx and AI methods to increase data availability for LCI and MR EEIO data, methods from other fields that could also be helpful were not included. For example, the field of operation research may offer techniques that could further expand possibilities for data generation, and the same could be said of subfields of AI that were not directly investigated such as image recognition. Moreover, CAx predominantly focuses on manufacturing of complex products and chemicals. Agricultural production is therefore not well represented in the analysis for CAx in chapter 5. At the same time, simulations tools specific for the agricultural sector do exist and should be further investigated to understand whether they could be used to generate data for LCI robustly. Also, chapter 5 did not include studies that showed methods of direct data collection from industrial actors. This was a conscious choice as we were interested in how to obtain data independently from direct collection from industrial actors. However, there are many interesting developments that could be of great benefit for data collection for circular economy assessment as shown also by Rusch et al., (2023). Future research should also be dedicated to finding how direct data collection may be possible from industrial actors, how National Statistical Offices may integrate this data for the purpose of CE, and how industrial secrecy and intellectual property rights could be protected. With regards to this last point, care should be given when simulating production systems independently from industries as some industrial actors may be litigious toward people who unravel details of their productions (Goldstein & Newell, 2019). Additionally, while we tried to investigate how to improve product detail of MR EEIO data through the expansion of LCIs, we did not research ways of increasing regional detail. Regional detail is important to identify where impacts may occur as a result of CE implementation.

At last, chapter 6 presented potential applications of digital technologies and AI from experts' knowledge and from partial scientific literature. Future research could provide more in-depth reviews (e.g., through systematic reviews) on these topics and offer exemplification of recommendations so that they can be more easily implemented by the scientific community.

7.4 IMPLICATIONS AND REFLECTIONS

In recent years there have been many policy developments at different levels aimed at increasing data availability, quality, and accessibility. For example, national statistical offices, EUROSTAT, and supranational organizations such as the Organization for Economic Co-operation and Development (OECD), United Nations Statistics Division (UNSTATS) and United Nations Environment Programme (UNEP) have supported the development of multiple platforms to facilitate the diffusion and comprehension of official statistics. Examples of this are the OECD data portal, UN COMTRADE and the World Environment Situation Room (WESR) respectively. This trend appears to likely continue as the need for insights into the sustainability of our economy in relation to the ecological crisis is crucial for science-based policy making and for informing the public. In the meantime, policies concerning CE are in the processes of being implemented, and they will influence the way we collect, store, and use data. For instance, in the context of the EU Digital Strategy (European Commission, 2022), the European Strategy for Data (European Commission, 2020) and the New Circular Economy Action Plan (European Commission, 2020), the European Commission is set to create CE dataspaces which will store information on circularity, potential for disassembly and sustainability of products. Additionally, the EU Carbon Border Adjustment Mechanism will also require the collection of data on material composition and GHG emissions of products and validation methods by authorities and specialists. These are just a few of the crucial environmental policies for which improved data is needed. However, these ambitions will fall short if insufficiently supported in terms of governance and funding. For this purpose, national and international organizations should be engaged in the process of harmonizing data practices across regions, in the institutionalization of data collection practices to support these ambitious policies, to provide a clearer picture of how we use natural resources and the impacts across the life cycle of products and services. This would greatly benefit society ability to tackle the ecological crisis and help us to transition to a sustainable and circular economic system. The path forward is not void of challenges, but the active management of these development should help us in mitigating these challenges and promote the benefits. The work presented in this thesis aims to provide a humble contribution to these developments.

Reference

Aguilar-Hernandez, G. A., Sigüenza-Sanchez, C. P., Donati, F., Merciai, S., Schmidt, J., Rodrigues, J. F. D., & Tukker, A. (2019). *The circularity gap of nations: A multiregional analysis of waste generation, recovery, and stock depletion in 2011. Resources, Conservation and Recycling, 151.* https://doi.org/10.1016/j.resconrec.2019.104452

Augspurger, T., Malliaraki, E., & Hopkins, J. (2023). *Open Source in Environmental Sustainability.*

Colloricchio, A., Sigüenza, C. P., Sollitto, F., Ahmed, Y., Pabon, C., & Bonja, V. (2023). *The circularity gap report 2023: Methods (v 1.0).* Circle Economy. https://www.circularity-gap.world/methodology

Creutzig, F., Niamir, L., Bai, X. et al. Demand-side solutions to climate change mitigation consistent with high levels of well-being. *Nat. Clim. Chang*. 12, 36–46 (2022). https://doi.org/10.1038/s41558-021-01219-y

Di Domenico, L., Safarzynska, K., & Raberto, M. (2022). *Resource Scarcity, Circular Economy and the Energy Rebound: A Macro-Evolutionary Input-Output Model* (SSRN Scholarly Paper No. 4266965). https://doi.org/10.2139/ssrn.4266965

Donati, F., Merciai, S., Deetman, S., Aguillar-Hernandez, G., Rietveld, W., Bastein, A. G. T. M., Boonman, H. J., Melo, F., & Hauck, M. (2021). *Learning from circular economy relevant modelling approaches.* TNO. https://repository.tno.nl/islandora/object/uuid%3A84ee54eb-311e-4246-aae3-07516eb3faf3

COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS A European strategy for data, (2020) (testimony of European Commission). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0066

COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS A new Circular Economy Action Plan For a cleaner and more competitive Europe, European Commission (2020) (testimony of European Commission). https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1583933814386&uri=COM:2020:98:FIN

European Commission. (2022). *European Commission Digital Strategy*. European Commission - European Commission. https://ec.europa.eu/info/publications/EC-Digital-Strategy_en

EUROSTAT. (2022). *Circular economy—Material flows.* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Circular_economy_-_material_flows

Hoekstra, R. (2019). *Replacing GDP by 2030: Towards a Common Language for the Well-being and Sustainability Community*. Cambridge University Press. https://doi.org/10.1017/9781108608558

ISO. (2023). *ISO/DIS 59020*. ISO. https://www.iso.org/standard/80650.html

Lange, K. P. H., Korevaar, G., Oskam, I. F., Nikolic, I., & Herder, P. M. (2021). Agent-based modelling and simulation for circular business model experimentation. *Resources, Conservation & Recycling Advances, 12,* 200055. https://doi.org/10.1016/j.rcradv.2021.200055

Leontief, W. (1970). Environmental Repercussions and the Economic Structure: An Input-Output Approach. *The Review of Economics and Statistics, 52(*3), 262–271. https://doi.org/10.2307/1926294

O'Neill, D. W., Fanning, A. L., Lamb, W. F., & Steinberger, J. K. (2018). A good life for all within planetary boundaries. *Nature Sustainability, 1*(2), Article 2. https://doi.org/10.1038/s41893-018-0021-4

Rusch, M., Schöggl, J.-P., & Baumgartner, R. J. (2023). Application of digital technologies for sustainable product management in a circular economy: A review. *Business Strategy and the Environment, 32*(3), 1159–1174. https://doi.org/10.1002/bse.3099

Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., & Kendall, A. (2019). A taxonomy of circular economy indicators. *Journal of Cleaner Production, 207,* 542–559. https://doi.org/10.1016/j.jclepro.2018.10.014

Walzberg, J., Lonca, G., Hanes, R. J., Eberle, A. L., Carpenter, A., & Heath, G. A. (2021). Do We Need a New Sustainability Assessment Method for the Circular Economy? A Critical Literature Review. *Frontiers in Sustainability, 1.* https://www.frontiersin.org/articles/10.3389/frsus.2020.620047

Wiebe, K. S., Bjelle, E. L., Többen, J., & Wood, R. (2018). Implementing exogenous scenarios in a global MRIO model for the estimation of future environmental footprints. *Journal of Economic Structures, 7*(1). https://doi.org/10.1186/s40008-018-0118-y

Winning, M., Calzadilla, A., Bleischwitz, R., & Nechifor, V. (2017). Towards a circular economy: Insights based on the development of the global ENGAGE-materials model and evidence for the iron and steel industry. *International Economics and Economic Policy, 14*(3), 383–407. https://doi.org/10.1007/s10368-017-0385-3

Goldstein, Benjamin, and Joshua P. Newell. 2019. "Why Academics Should Study the Supply Chains of Individual Corporations." *Journal of Industrial Ecology.* https://doi.org/10.1111/jiec.12932.

SUMMARY

The circular economy (CE) is an industrial economic paradigm promoted with the aim to minimize the absolute consumption of resources, and the emission of pollutants while ensuring optimal socio-economic performance. This aim is pursued through multiple technical (e.g., business model changes and novel technology implementation) and policy approaches (e.g., changes in regulations to promote or limit certain activities). There is great diversity of circular economy strategies and the degree of implementation may vary greatly depending on the local industrial conditions, households behaviors and the ambitions of policy makers. Some of the key CE strategies include Product Lifetime Extension, Resource Efficiency, Closing Supply Chain Loops and Residual Waste Management. The structure of the global production and consumption system to which an economy or industry is connected plays an important role in how the impacts of implementation of CE strategies play out. For example, while circular economy strategies in the Netherlands could result in a longer product lives and more jobs in the repair sector, they may result in worse economic performance abroad in countries where primary production is located. Assessing the size of economic, social and environmental performances in exporting countries is helpful to understand the implications of implementation of circular economy strategies across the international system of consumption and production. Such insights are necessary to fully understand the benefits and barriers of policy and technical implementation, as changes in one sector or region will inevitably cascade across global supply chains. At the same time, environmental pressures are very diverse, and optimization to reduce emissions on one side could results in higher resource extractions or other unintended impacts (see chapter 2). In sum, economic, social and environmental impacts of CE measures in a specific country or sectors can be spread geographically, are interconnected and are diversified in type. Therefore, it is important to understand potential trade-offs of CE strategies. This thesis hence puts the question central how the economic and environmental effects of CE strategies can be assessed and the detailed data needed in such assessments can be obtained.

In chapter 2 we showed how the analysis of economic and environmental trade-offs may be performed for the agricultural sector. *Multi-Regional*

Environmentally Extended Input-Output Analysis (MR EEIOA) is a very suitable tool for this purpose, as it allows to perform analyses such as hotspot and footprint analysis of product groups and parts of the value chains which are responsible for high level of environmental impacts. The data underlying MR EEIOA (i.e., MR EEIO tables) is based on economic Input-Output (IO) tables. Such tables divide the economy of a country in a number of sectors (or products) and their inputs (e.g., services, goods and employment) required for the supply of goods and services to other industries and final consumers. The difference between the consumption of all products and services by an industry and its output is value added (i.e., .e. the sum of wages, taxes and subsidies and profit). The sum of all value added by industry by country defines the Gross Domestic Product (GDP). When IO tables of multiple countries are combined together connecting them through their trade relationships, this results in a multi-regional IO system, which in principle can cover all countries and all sectors in the global economy (i.e., Global MRIO). So, a global MRIO covers global value chains, social information like numbers of jobs, economic information like value added. If a MRIO system (global, subnational or otherwise), comes with a set of environmental extensions, it is referred to as a MR EEIO system. This MR EEIO data in combination with analytical methods such as footprint and hotspot analysis are a suitable starting point for developing improvement options such as CE interventions.

There are however challenges in the employment of MR EEIO for analyzing the impacts of CE strategies. For example, scenario modelling software is not easily accessible. Scenario data often cannot be reused due to opaqueness of used inputs and how they are implemented to construct counterfactual scenarios. These challenges motivated the second study presented in this thesis in chapter 3, for which we developed a software in Python called pycirk, through which policy analysts can create complex scenarios and analyze their results. In addition to that, we provided a standardization of how CE strategies for product life extension and resource efficiency may be implemented as starting point to begin providing clarity and transparency on how these scenarios can be constructed. The tool allows for scenario settings in the software to be easily shared across different types of users and in publications thanks to their standardized structure and readability. For this study we also performed an analysis on product life extension and resource efficiency measures concerning the use and manufacturing of durable products (i.e., machineries and vehicles) and constructions. The presented software and methods were used to perform the analysis, which highlighted limitations and potential uses. For instance, assumptions had to be made in lack of detailed information on product categories that are typically aggregated in MR EEIO databases. Additionally, while standardized methods provided guidance in the modelling of the interventions, adaptation was still needed in some cases.

While the *pycirk* software facilitated various scenario analysis operations, it still had a high entry level for practitioners without a computer science background and lacked a graphical user interface for immediate visualization of results. For this reason, as described in chapter 4 the RaMa-Scene web-application was developed (https://www.ramascene.eu). The chapter presents a web-application with a graphical user interface that would be accessible by anyone with an internet connection and through which it would be possible to construct complex scenarios and quickly visualize and download their results, thereby lowering the entry level to access MR EEIO data. Since its deployment, RaMa-Scene has been used in classrooms and by consultants to study socio-economic and environmental impacts of products and potential policy implementations.

However, both in chapter 3 as chapter 4 we found MR EEIO data only allow modelling CE strategies such as Product Life time extension and Resource Efficiency strategies. MR EEIO tables currently are insufficient detailed to model Closing supply chain loops. This requires a very high product and even component level resolution to simulate the re-use of products and components central in this CE strategy. Furthermore, MR EEIO also describes the economy in monetary terms, while particularly for CE strategies such as Residual waste management a physical MR EEIO would give more insightful results. Product categories in MR EEIO data are often aggregates of different products (e.g. mobile phones, PCs etc. combined to electrical and electronic products) and, sometimes, their services. Circular economy interventions and their changes often affect specific relationships in supply chains and regions, which pushes the limits of applicability of input-output methods. However, as indicated MR EEIO tables have the advantage of giving a comprehensive representation of the interconnected relationships of economies and industries across the globe, something that is typically not possible to obtain from other types of databases such as those used for Life Cycle Assessment (LCA) or trade analysis. In other words, during the time span in which this thesis was written (2017-2022) the choice between databases for economic and environmental analysis presented important tradeoffs between detail and comprehensiveness of data. Some authors have tried to employ hybrid methods to compensate shortcomings in data and methods. Such hybrid LCA methods make use of the rather aggregated MR EEIO data as background data, and detailed Life Cycle Inventory data for foreground data. This type of hybridization is convenient as LCA and IO methods share similar computational methods, and LCI data in some cases is used to detail MR EEIO databases or to estimate environmental extensions. However, data collection at the level of detail required to assess impacts of existing supply chains and model the changes of circular economy interventions is a time consuming and labor intensive practice, which sometimes also may be limited also by data confidentiality.

In the fifth chapter of this thesis, we investigated these challenges and described how Computer Aided Technologies (CAx) have been used to obtain information that can be useful to complete LCIs; and how Artificial Intelligence (AI) methods have been used to support data estimation where direct data collection or simulation was not possible or impractical, and data conversion from a variety of sources. This work not only contributes to the expansion of LCI data, but it also promotes a stronger integration of LCA with open source software used for product design, and contributes to the development of digital twins of supply chains. These data and systems could then be used to increase the product and industry detail of EEIO databases, promoting an ever more seamless transition from LCI and MR EEIO data. However, while simulations of production systems and supply chains, and the conversion of heterogenous domain specific data and knowledge for LCA and MR EEIO can be an important source of data for CE, more coordination is needed to make the best use of the current digital infrastructure, expertise and automation methods to improve our ability to assess the socio-economic and environmental impacts of the circular economy. In this regard, the last paper of this thesis offers a perspective to the industrial ecology community on how to use digital technologies in combination with AI methods to support decision making for sustainability at all levels.

There are multiple limitations in the work presented in this thesis, which represent inspiration for future research. Firstly, while MR EEIO proved to be an effective tool to model CE interventions for Product Life extension and Resource efficiency strategies, as discussed above is not yet well suited to model Closing supply chain loops or Residual waste treatment options, recycling and changes in material stocks due to the lack of physical data on production and consumption, next to a lack of detail in product and component resolution. Hybrid MR EEIO and waste IO would allow to better capture physical aspects concerning the CE. Future research should expand the use of tools for CE assessment to include hybrid and more detailed MR EEIO data. Additionally, while many types of environmental, social and economic impacts can be assessed with MR EEIO databases, this framework has hardly been linked to the concept of planetary and social boundaries. That is important to understand if CE strategies bring us within an environmentally safe and socio-economically just space. Future research could investigate how to integrate quantifiable social and planetary boundaries into easy-to-use tools such as RaMa-Scene. Furthermore, the demand driven model at the base of our approaches is a linear model. We know, however, that socio-economic and environmental dynamics can be complex and non-linear. The hybridization of static with dynamic models may provide additional insights into CE that are simply out of reach for linear models such as the Leontief model. While we investigated CAx and AI methods to increase detail in data availability for LCI and MR EEIO data, methods from other fields that could also be helpful were not included. Similarly, we did not research ways of increasing regional detail.

The recent developments from national statistical offices and supranational organization to increase diffusion and use of official statistics will likely continue and as the need for insights into the sustainability of our economy in relation to the ecological crisis, more and more effective tools for data and scenario exploration (e.g., for circular economy and sustainability assessment) will be need. In the meantime policies concerning CE are in the processes of being implemented, and they will influence the way we collect, store and use data. For instance, in the context of the EU Digital Strategy, the European Strategy for Data and the New Circular Economy Action Plan, the European Commission is set to create CE dataspaces which will store information on circularity, potential for disassembly and sustainability of products. However, these ambitions will fall short if insufficiently supported in terms of governance and funding. For this purpose, national and international organizations should be engaged in the process of harmonizing data practices across regions, in the institutionalization of data collection practices to support these ambitious policies, to provide a clearer picture of how we use natural resources and the impacts across the life cycle of products and services. This would greatly benefit society ability to tackle the ecological crisis and help us to transition to a sustainable and circular economic system. The path forward is not void of challenges but the active management of these development should help us in mitigating these challenges and promote the benefits. The work presented in this thesis aims to provide a humble contribution to these developments.

SAMENVATTING

De circulaire economie (CE) is een industrieel-economisch paradigma dat wordt gepromoot met het doel het absolute verbruik van hulpbronnen en de uitstoot van verontreinigende stoffen te minimaliseren en tegelijk optimale sociaaleconomische prestaties te garanderen. Dit doel wordt nagestreefd door middel van diverse technisch-bedrijfskundig (bv. verandering van business model en toepassing van nieuwe technologie en design) en beleidsbenaderingen (bv. wijziging van regelgeving om bepaalde activiteiten te bevorderen of te beperken). Er bestaat een grote verscheidenheid aan strategieën voor een circulaire economie en de specifieke uitvoering kan sterk variëren, afhankelijk van het type product, het productieproces, de acceptatie door huishoudens en de inzet van beleidsmakers. Enkele van de belangrijkste CE-strategieën zijn verlenging van de levensduur van producten, efficiënt gebruik van hulpbronnen, het hergebruik van producten, componenten en materialen door middel van ketensluiting en hoogwaardig verwerken van restafval. Daarnaast is het van belang hoe de lokale economie is ingebed in het mondiale productie- en consumptiesysteem. Zo kunnen strategieën voor een circulaire economie in Nederland weliswaar hier leiden tot langer gebruik van producten en meer werk ten aanzien van reparatie, maar tot verlies aan banen en toegevoegde waarde elders als die producten in het buitland worden gemaakt. Het analyseren van de economische, sociale en milieuprestaties in exporterende landen is nuttig om de gevolgen van de uitvoering van strategieën voor een circulaire economie in het hele internationale consumptie- en productiesysteem te begrijpen. Dergelijke inzichten zijn nodig om de voor- en nadelen van circulaire strategieën volledig te begrijpen, aangezien veranderingen in één sector of regio onvermijdelijk een kettingreactie teweeg brengt in de mondiale toeleveringsketens. Tegelijkertijd is de geven productie-consumptieketens een heel diverse soorten van milieudruk. Vermindering van één type milieudruk leidt soms tot verhoging van een ander type, of andere onbedoelde effecten (zie hoofdstuk 2). Kortom, de economische, sociale en milieueffecten van CE-maatregelen in een specifiek land of een specifieke sector hebben een geografische doorwerking en zijn van uiteenlopende aard waarbij probleemafwenteling op de loer ligt. Dit proefschrift stelt zich daarom de vraag op welke manier de economische en duurzaamheidseffecten van CE-strategieën in kaart kunnen worden gebracht en hoe de daarvoor benodigde gedetailleerde data verkregen kan worden.

In hoofdstuk 2 hebben wij laten zien hoe de analyse van economische en ecologische trade-offs kan worden uitgevoerd voor de landbouwsector. Multi-Regionale Milieukundige Input Output Analyse (in het Engels: Environmentally Extended Input-Output Analysis (MR EEIOA) is hiervoor een zeer geschikt instrument.De gegevens die ten grondslag liggen aan MR EEIOA (d.w.z. MR EEIO-tabellen) zijn gebaseerd op economische input-outputtabellen (IO-tabellen). Dergelijke tabellen verdelen de economie van een land in een aantal sectoren (of producten) en hun inputs (bv. diensten, goederen en werkgelegenheid) die nodig zijn voor de levering van goederen en diensten aan andere sectoren en eindverbruikers. Het verschil tussen het verbruik van alle producten en diensten door een industrie en haar output is de toegevoegde waarde (d.w.z. de som van lonen, belastingen en subsidies en winst). De som van alle toegevoegde waarde per bedrijfstak per land bepaalt het Bruto Binnenlands Product (BBP). Wanneer IO-tabellen van meerdere landen worden gecombineerd en met elkaar worden verbonden via hun handelsbetrekkingen, resulteert dit in een multiregionaal IO-systeem, dat in principe alle landen en alle sectoren in de wereldeconomie kan bestrijken (d.w.z. wereldwijde MRIO). Een mondiaal MRIO omvat dus mondiale waardeketens, sociale informatie zoals het aantal banen, economische informatie zoals toegevoegde waarde. Indien een MRIO-systeem (mondiaal, subnationaal of anderszins) vergezeld gaat van een reeks milieu-uitbreidingen, wordt het een MR EEIO-systeem genoemd. Deze structuur van MR EE IO tabellen maakt het mogelijk om de milieuvoetafdruk van productgroepen en delen van waardenketens vast te stellen, en ook in welke stappen van de keten de meeste milieudruk wordt gegenereerd (de zogenaamde hot spots). Dit vormt weer een geschikt uitgangspunt voor het ontwikkelen van verbeteropties zoals CE interventies

Het gebruik van MR EEIO voor het analyseren van de effecten van CE-strategieën is echter niet zonder problemen. Software voor scenariomodellering is bijvoorbeeld niet gemakkelijk toegankelijk. Scenariogegevens kunnen vaak niet worden hergebruikt vanwege de ondoorzichtigheid van de gebruikte inputs en de manier waarop deze worden geïmplementeerd om zogenaamde ‘counterfactual’ scenario's te construeren. Deze punten waren aanleiding voor de tweede studie in dit proefschrift in hoofdstuk 3, waarin we software hebben ontwikkeld waarmee beleidsanalisten complexe CE scenario's kunnen maken en de resultaten ervan kunnen analyseren. De software is ontwikkeld in Python en noemden we ‘pycirk’. Daarnaast is er een standaard protocol ontwikkeld voor de manier waarop CE-strategieën voor productlevensduurverlenging en hulpbronnenefficiëntie kunnen worden geïmplementeerd in MR EEIO tabellen. Dit helpt bij het transparant construeren van dit type CE scenario’s. Dankzij de gestandaardiseerde structuur kunnen de scenario-instellingen in de software gemakkelijk worden gedeeld met andere gebruikers en analysten en in publicaties. Voor deze studie hebben we ook een case studie uitgevoerd over verlenging van de levensduur van producten en maatregelen voor een efficiënt gebruik van hulpbronnen bij het gebruik en de vervaardiging van duurzame producten (d.w.z. machines en voertuigen) en constructies. Deze studie gaf ook de beperkingen van de aanpak aan. Zo moesten bepaalde productcategorieën handmatig worden gedisaggregeerd omdat de data in beschikbare MR EEIO databases te generiek bleken.

Hoewel de pycirk-software dus verschillende scenarioanalyses voor CE mogelijk maakte, was het onvoldoende gebruiksvriendelijk. Een grafische gebruikersinterface voor invoer van scenario-parameters en directe visualisatie van resultaten was gewenst om de toegankelijkheid voor voor praktijkmensen zonder een achtergrond in softwareontwikkeling. Daarom werd, zoals beschreven in hoofdstuk 4, de RaMa-Scene web-applicatie ontwikkeld (https://www.ramascene.eu). Dit hoofdstuk presenteert een web-applicatie met een grafische gebruikersinterface die toegankelijk is voor iedereen met een internetverbinding en waarmee het mogelijk is complexe scenario's te construeren en de resultaten ervan snel te visualiseren en te downloaden, waardoor het werken met MR EEIO-gegevens enorm vergemakkelijkt wordt. Sinds de invoering ervan is RaMa-Scene gebruikt in universitaire cursussen en door consultants om de sociaal-economische en milieueffecten van producten en mogelijke beleidsimplementaties te bestuderen.

Zowel in hoofdstuk 3 als in hoofdstuk 4 constateerden wij dat met MR EEIO-gegevens alleen CE-strategieën zoals verlenging van de productlevensduur en strategieën voor efficiënt hulpbronnengebruik kunnen worden gemodelleerd. MR EEIO-tabellen zijn momenteel onvoldoende gedetailleerd om bijvoorbeeld hergebruik van producten, componenten of materialen (ofwel: ketensluiting) te modelleren, omdat het hier om zeer product- of zelfs component en materiaal-specifieke opties gaat. Het modelleren van deze CE strategie vereist dus vereist een zeer hoge resolutie op product- en zelfs component- en materiaalniveau. Bovendien beschrijft MR EEIO de economie in de eerste plaats in monetaire termen. Voor restafval geeft een geldwaarde vaak geen goede reflectie van het fysieke afvalvolume. Juist dit fysieke afvalvolume is van belang bij het doorrekenen van opties voor hoogwaardige verwerking van restafval, dus voor deze CE strategie zou een fysieke MR EEIO meer inzichtelijke resultaten zou geven. Productcategorieën in MR EEIO-gegevens zijn vaak aggregaten van verschillende producten (bv. mobiele telefoons, pc's enz. worden gecombineerd tot elektrische en elektronische producten). Dit is een detailniveau wat in MR EEIO tabellen, die de economie normaal in maximaal 100-150 productgroepen opdelen, onmogelijk kan worden gehaald. Zoals aangegeven hebben EEIO-tabellen echter het voordeel dat zij een volledig beeld geven van de onderlinge relaties van economieën en industrieën over de hele wereld, iets wat doorgaans niet mogelijk is met andere soorten databronnen zoals die welke voor Levenscyclusanalyse van producten (LCA) of handelsanalyse worden gebruikt. Met andere woorden, in de periode waarin dit proefschrift werd geschreven (2017-2022) was er qua keuze tussen databases voor economische en milieuanalyse altijd een afweging te maken tussen detail en volledigheid van de gegevens. Sommige auteurs hebben geprobeerd hybride methoden toe te passen om met de tekortkomingen van databases om te gaan. Dergelijke hybride LCA-methoden gebruiken de relatief geaggregeerde MR EEIO-gegevens als achtergrond, en gedetailleerde Life Cycle Inventory-gegevens als voorgrond. Dit type hybridisatie is handig omdat LCA- en IO-methoden de milieuvoetafdruk op een vergelijkbare manier berekenen, en LCI-gegevens in sommige gevallen worden gebruikt om MR EEIO-databases te detailleren of om milieu-extensies te schatten. Het verzamelen van gegevens op het detailniveau dat nodig is om de effecten CE strategieën zoals ketensluiting en hoogwaardige afvalverwerking te beoordelen, is echter tijdrovend. Verder zijn de mogelijkheid om data te verkrijgen vaak ook beperkt on redenen van vertrouwelijkheid.

In het vijfde hoofdstuk van dit proefschrift hebben we daarom onderzocht hoe Computer-Aided Technologies (CAx) en Artificial Intelligence (AI) kunnen worden gebruikt om gegevens uit verschillende bronnen te converteren en/of LCI data te kunnen schatten. Dit werk helpt niet alleen bij de uitbreiding van LCI databases, maar bevordert ook een sterkere integratie van LCA met open source software die wordt gebruikt voor productontwerp, en draagt bij tot de ontwikkeling van 'digital twins' van productieprocessen in toeleveringsketens. Deze gegevens en systemen kunnen vervolgens worden gebruikt om het detail van EEIO databases qua producten en industrieën te verhogen, zodat zij steeds meer het niveau van detail van LCIs benaderen. Maar er is ook meer coördinatie nodig om optimaal gebruik te maken van de huidige digitale infrastructuur, expertise en automatiseringsmethoden om ons vermogen om de sociaaleconomische en milieueffecten van de circulaire economie te beoordelen, te verbeteren. Het laatste artikel van dit proefschrift beschrijft daarom hoe de gemeenschap van Industrieel Ecologen digitale technologieën in combinatie met AI-methoden kunnen worden gebruiken om de besluitvorming rond duurzaamheidsvraagstukken op alle niveaus te ondersteunen.

Er zijn verschillende beperkingen in het werk dat in dit proefschrift is gepresenteerd, die inspiratie bieden voor toekomstig onderzoek. Ten eerste is MR EEIO weliswaar een effectief instrument gebleken om CE-interventies te modelleren voor strategieën zoals levensduurverlenging en voor efficiënt gebruik van hulpbronnen. Zoals hierboven besproken is het echter nog niet goed geschikt voor het modelleren van ketensluiting of hoogwaardig verwerken van restafval. Ook schiet MR EEIO in praktijk tekort in het meten van veranderingen in materiaalvoorraden. Deze beperkingen komen voort uit het gebrek aan fysieke gegevens over productie en verbruik van producten, naast een gebrek aan detail in de resolutie van producten en productiesectoren. Hybride MR EEIO en fysieke MR EEIO kunnen het mogelijk maken de fysieke aspecten van de economie beter in kaart te brengen, en daarmee een betere basis bieden voor werk rond CE scenarios. Toekomstig onderzoek moet het gebruik van instrumenten voor de beoordeling van CE uitbreiden met hybride en meer gedetailleerde MR EEIO-gegevens. Ten tweede, hoewel vele soorten ecologische, sociale en economische effecten kunnen worden beoordeeld met MR EEIO-databases, is dit kader nog nauwelijks gekoppeld aan het concept van planetaire en sociale grenzen. Dat is belangrijk om te begrijpen of CE-strategieën ons binnen een ecologisch veilige en sociaal-economisch rechtvaardige ruimte brengen. Toekomstig onderzoek zou kunnen nagaan hoe gekwantificeerde sociale en planetaire grenzen kunnen worden geïntegreerd in gebruiksvriendelijke instrumenten zoals RaMa-Scene.

Ten derde zijn de MR EEIO en LCI databases die aan de basis liggen van onze aanpak in essentie lineair. Wij weten echter dat de sociaal-economische en milieudynamiek complex en niet-lineair kan zijn. De hybridisatie van statische met dynamische modellen kan extra inzichten rond CE scenario's opleveren die voor lineaire modellen zoals het Leontief-model eenvoudigweg buiten bereik liggen. En ten vierde, ons onderzoek rond CAx- en AI-methoden om de beschikbaarheid van gegevens voor LCI en MR EEIO-gegevens te vergroten kent beperkingen. Potentieel nuttige methoden uit andere vakgebieden zijn niet meegenomen. Evenmin hebben wij manieren onderzocht om het regionale detail qua productie en gebruik van producten te vergroten.

Naarmate de behoefte aan inzicht in de duurzaamheid van onze economie in relatie tot de ecologische crisis toeneemt, zullen meer en effectievere instrumenten voor gegevens- en scenarioverkenning (bv. voor circulaire economie en duurzaamheidsbeoordeling) nodig zijn. Dit geldt ook voor data die nodig zijn voor CE beleid. In het kader van de digitale strategie van de EU, de Europese datastrategie en het EU Actieplan voor de Circulaire Economie is de Europese Commissie bijvoorbeeld van plan 'CE- dataspaces' te creëren waarin informatie over circulariteit, demontagemogelijkheden en duurzaamheid van producten wordt opgeslagen. Deze ambities schieten echter tekort als ze onvoldoende ondersteund worden in termen van governance en financiering. Idealiter worden nationale en internationale statistische organisaties betrokken bij een proces van harmonisatie en institutionalisatie van gegevensverzameling in verschillende globale regio's. Dit kan een veel beter beeld geven van de manier waarop wij natuurlijke hulpbronnen gebruiken en van de effecten gedurende de levenscyclus van producten en diensten. De weg voorwaarts is niet vrij van uitdagingen. Het in dit proefschrift gepresenteerde werk beoogt een bescheiden bijdrage te leveren aan het oplossen daarvan.

CURRICULUM VITAE

Franco Donati was born in Sassari, Italy where he obtained a high school diploma from the trade school “Istituto Statale D’Arte Filippo Figari” with a focus on photography and graphic design in 2005.

In 2010, he obtained a bachelor's degree in industrial design from the Polytechnic of Turin (Italy) under the faculty of Architecture. His graduation thesis was titled “The eco-sustainability of toys: meta-analysis and validation of design guidelines”.

From 2012 to 2014 he worked as product design engineer for the development of renewable energy technologies in Santa Barbara, California (USA) with a special focus on solar and marine technologies such as residential heating and wave energy converters.

In 2014, he moved to the Netherlands to participate in the MSc of Industrial Ecology where he graduated in 2017 with a thesis titled “Modelling the Circular Economy in Environmentally Extended Input-Output”.

In 2017, he began his work as a PhD student at Leiden University Institute of Environmental Sciences (CML) of which this thesis is the outcome. During his PhD he acted as project manager of the RaMa-Scene project funded by the European Institute of Technology (EIT) RawMaterials.

In July 2021 he began working as a researcher in the Getting the Data Right project funded by the Danish KR Foundation, where he continues investigating ways of facilitating and promoting accessibility of detailed data on the economy and the environment for the purpose of sustainability policies.

In 2022 he began working as a Data Editor for the Journal of Industrial Ecology and acquired together with Dr. Stefano Cucurachi the EU funded project H2Steel concerning the environmental assessment at micro and macro level of novel technologies for the use of hydrogen in steel manufacturing.

LIST OF PUBLICATIONS

Donati, F., Dente, S. M. R., Li, C., Vilaysouk, X., Froemelt, A., Nishant, R., Liu, G., Tukker, A., & Hashimoto, S. (2022). The future of artificial intelligence in the context of industrial ecology. Journal of Industrial Ecology, 00, 1– 7. https://doi.org/10.1111/jiec.13313

Donati, F., Tukker, A. Environmental Pressures and Value Added Related to Imports and Exports of the Dutch Agricultural Sector. Sustainability 2022, 14, 6057. https://doi.org/10.3390/su14106057

Donati F., Niccolson S.I., Koning A. de, Daniels B., Christis M., Boonen K., Geerken T., Dias Rodrigues J.F. & Tukker A. (2021), Modeling the circular economy in environmentally extended input-output: a web application, Journal of Industrial Ecology 25(1): 36-50.

Donati F. & Tukker A. (2020), Milieudruk Nederlandse landbouwimport groter dan die van de -export, ESB news 105(4791S): 12-17.

Donati F., Aguilar-Hernandez G.A., Sigüenza-Sánchez C.P., Koning A. de, Dias Rodrigues J.F. & Tukker A. (2020), Modeling the circular economy in environmentally extended input-output tables: Methods, software and case study, Resources Conservation and Recycling 152: 104508.

Cetinay Iyicil H., **Donati F**., Heijungs R. & Sprecher B. (2020), Efficient computation of environmentally extended input-output scenario and circular economy modeling, Journal of Industrial Ecology 24(5): 976-985.

Aguilar-Hernandez G.A., Siguenza -Sanchez C.P., **Donati F.**, Merciai S., Schmidt J., Dias Rodrigues J.F. & Tukker A. (2019), The circularity gap of nations: A multiregional analysis of waste generation, recovery, and stock depletion in 2011, Resources, Conservation and Recycling 151: 104452.

Aguilar-Hernandez G.A., Sigüenza-Sanchez C.P., **Donati F.**, Rodrigues J.F.D. & Tukker A. (2018), Assessing circularity interventions: a review of EEIOA-based studies, Journal of Economic Structures 7(14): 1-24.

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