Expanding the coverage of ecosystem services in life cycle assessment: an interdisciplinary venture

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Preface

At the beginning of every PhD journey, there are several questions awaiting to be answered. There are those questions mold by the researcher in training, the PhD candidate along with their supervisors and team, and, in other instances, questions that arise at different stages of development in the life of a researcher. The origins of the questions we tackle, are all rooted in a desire to understand the reality that surrounds us, an attempt to explain it, or at least, to envision a way in which we can actively describe and influence the elaborated mantelpiece of facts and conjectures we witness while doing science. In my case, the questions that led to the start of this journey to become a trained researcher on environmental sciences, came in the middle of the Caribbean Sea, while volunteering in an oceanographic research cruise where physicists and oceanographers had begun modelling underwater currents to help provide information on the possible extent of the disastrous Deepwater Horizon oil spillage, where an estimated amount of 780,000 m^3 of crude oil leaked to the sea.

By the time I enrolled as volunteer for this research cruise, I had been majoring in Biology. My specialization track had been biomedicine, and while training at the immunology lab, the amount of time I was spending looking through microscope and tubes had become larger than the time I had spent looking out the window. Despite the unhealthy sleeping and eating habits of most of those who work full time in a biology lab, I was satisfied with the job I was doing, studying the different mechanisms the body uses to heal itself, and the ways we can engineer molecular and cellular systems to help us in the fight against yet unconquerable diseases. Working in biological labs involves not only training on specialized techniques, but also on safety procedures and guidelines. One night staying until late at the lab waiting for a sample, I started wandering around the isles, looking at the labels on all the different bottles and containers we regularly used. The black and red labels, all indicating different effects and risks associated with the substances inside, carcinogenic, mutagenic, toxic. It is not only important to know how to handle these substances, but it is of even higher importance to know how to dispose of them in a safe manner. The questions arose in my mind after contemplating at these labels: *What happens to all this waste, where does it end if disposed carelessly?* Skepticism or simple realism, but it was hard for me to believe that all these heavily toxic and pollutant materials were correctly dealt with in my country, let alone all around the world. How much work in the lab trying to cure a disease could compensate for all the unintended consequences of the instruments we use and their collateral damage? The question remained unconsciously in a corner of my mind. As a stone in the shoe, I kept walking without putting too much thought on it. After all, I was focused on another task, one that I could address with the tools and studies I had chosen.

The vacancy for a paid volunteer job in an oceanographic cruise came as gift of destiny, through people I knew and at a time when both the experience and money were highly welcomed. That summer, I bought hard shell boots and packed my bags to spend more than 4 weeks ashore cruising on a research boat, helping with the small tasks onboard and cleaning measuring instruments that were extracted back from the ocean for maintenance and collection of data. Spending weeks out in the ocean has been one of the most fascinating experiences of my life, not only for the opportunity of seeing the Caribbean Sea blur its horizon line with a red scarlet sky, but also for the opportunity of being confronted once again with a question that had come to me before, and to which I had, partly, closed the door due to lack of experience and, I must admit, courage.

The Deepwater Horizon oil spillage was one of the largest documented disasters of recent times. Millions of gallons drained out of wells, thousands of animals washed ashore covered in black sludge. By the time of the spill, the only information that could help determine how far the spill could go and which potential routes it would take, were the studies from an oceanographic research group from Baja California that had been developing a numerical model to describe underwater currents in the Caribbean Sea. With an ecological disaster at hands, the funding for this research group increased to aid the strategies that would be put in place to attempt remediation and future prevention. The intersection of oceanographers, physicists, and many other disciplines involved in the project, were a first glimpse for me on the importance of interdisciplinary collaboration, and it woke up a question that was closely related with that old stone in my shoe: What if we could prevent, or at least attempt to foresee, with the same amount of strength in collaboration, the unintended consequences of our practices, and the risks to which we submit ourselves, and our surroundings?

To my mother, Amelia.

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Chapter 1

General Introduction

1.1 The unknown unknowns

It is widely agreed that human activities have left, to put it mildly, a soiled footprint around the globe, with widespread deforestation (Barbosa, Nabout, and Cunha 2023; FAO 2022; Pacheco et al. 2021), resource depletion (Oberle et al. 2019), soil erosion (Van Oost et al. 2007), water and air pollution (Fuller et al. 2022), as examples of extensively documented current environmental crises (Ceballos et al. 2015; Waters et al. 2016). Besides these strains, the total global population is expected to surpass 9 billion people by 2030, with an estimated increase of 30% of the population moving to urban areas (United Nations 2022). These growing demands from an increasing global population have not only exacerbated the degradation of natural resources, but also the challenges for a transition towards sustainable development (Kaiho 2023; Khorram-Manesh 2023). As a result, the United Nations published in 2015 a universal call for action focusing on a set of identified global goals, commonly known as the sustainable development goals (United Nations 2015). These goals describe humanity targets that aim at global peace, end of poverty and hunger, and among these, several pillars that are directly linked to the protection of the environment and the quality of natural resources (Yang et al. 2020; Yin et al. 2021).

To embrace these challenges, several sectors of society have mobilized the demand for the assessment of environmental impacts as an integral part of decision- and policy- making (Khorram-Manesh 2023), modifying current production systems to minimize negative impacts, and designing more resilient systems (Fiksel 2003; Wood et al. 2018). Assessing environmental impacts involves identifying and evaluating the potential effects of human activities on the natural environment, including air, water, soil, and wildlife (Qiu, Yu, and Huang 2022). By conducting a comprehensive assessment of environmental impacts, individuals, organizations, and governments can better understand the potential consequences of their actions and make informed decisions to mitigate or avoid harmful effects. This can help ensure that human activities are conducted in a manner that is compatible with the long-term health and well-being of the natural environment, which is essential for preserving biodiversity, protecting ecosystems, and maintaining the natural resources that sustain life on Earth (Barnosky et al. 2011).

1.2 The Ecosystem Service approach

Nowadays, the term ecosystem service is commonly used to address the natural resources and ecological processes that have been identified as beneficial for the sustenance of human wellbeing and the general interests of societies (Ainscough et al. 2019; Potschin and Haines-Young 2018). Several conceptual frameworks have been proposed to visualize the beneficial relations between ecosystems and society (Boyd and Banzhaf 2007; Fisher, Turner, and Morling 2009; Olander et al. 2021). In this thesis, I will refer to ecosystem services following the classification system proposed by the Common International Classification for Ecosystem Services (CICES), which presents three main categories (Figure 1.1): (i) provisioning services, which include resources directly obtained from ecosystems, such as biomass for food or materials, genetic resources and water; (ii) regulating services and maintenance, which are benefits obtained from the supporting ecological processes, including, but not limited to, climate regulation, soil erosion resistance, crop pollination, nutrient and water cycling; and (iii) cultural services, which includes the well-being and recreational benefits that people obtain from natural systems, such as knowledgeable systems, health and social relations, and aesthetic values (Haines-Young and Potschin 2018). Under other classification systems, such as the one presented by the Millenium Ecosystem Assessment (MEA 2005), regulatory and maintenance services are commonly listed as separate categories, with 'maintenance' services presented instead as 'supporting' services. However, these all refer to the same ecosystem services listed under a single category in the CICES classification, and which correspond to regulatory services, which help maintain and support human well-being and livable conditions (Mengist, Soromessa, and Feyisa 2020).

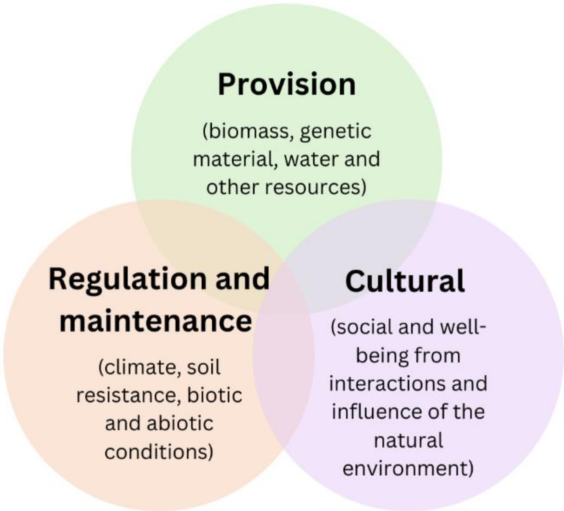

Figure 1.1 *The three main categories of ecosystem services as defined by the Common International Classification System of Ecosystem Services (CICES).*

The Millennium Ecosystem Assessment (MEA) was published in 2005 by the United Nations, as a result of a major international cooperation aimed at identifying, inventorying, and quantifying the state of multiple ecosystem services (Primmer et al. 2015). The results presented by the MEA report indicate that the majority of the ecosystem services identified showed severe degradation due to human activities, some to the degree of permanent or irreparable damage, and more than half currently managed under unsustainable practices (MEA

2005). In turn, the degradation of ecosystem services, which can be translated into social and economic damage, poses global risks for societies and human well-being (Costanza et al. 1998, 2014; Díaz et al. 2018; Van der Ploeg, De Groot, and Wang 2010).

Several factors, such as high demand of resources from an increasing urban population and short-term economic driven industrialization, have resulted in the unsustainable use and management of ecosystem services of all around the world (de Groot et al. 2012; Maes et al. 2012). Since the publication of the MEA report and the early economic valuation studies of ecosystem services (Costanza et al. 2014; de Groot et al. 2012; Reynaud and Lanzanova 2017) numerous efforts ranging from scientific to legislative, have focused on their assessment and protection (Aragão, Jacobs, and Cliquet 2016; McDonough et al. 2017), with the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) as a clear example of an initiative aimed at improving the understanding of ecosystem services and their interrelation with human activities and societies (Díaz et al. 2018; IPBES 2019).

To better assess impacts on ecosystem services, it is necessary to identify and quantify the mechanisms that drive them and the synergetic effects that can stimulate or hinder their provision (Perschke et al. 2023). Given the associated complexity of identifying key ecosystem services, and in particular those that are not directly linked to economic activities, many ecosystem services remain unaccounted for (Carrasco et al. 2014), with limited data available for a great part of those evaluated, and with several questions unresolved on the underlying processes that influence them and their effects on current and future generational needs (Ceballos et al. 2015).

Hence, effective policy and decision-making requires the aid of scientific research, by providing a better understanding and assessment of ecosystem services, and support guidelines towards more environmentally sustainable practices (Yin et al. 2021). In order to avoid 'cherry-picking' from a small sub-set of ecosystem services that could lead to negative consequences and unintended tradeoffs, it is important to concentrate efforts on the continuous identification and study of ecosystem services, and take on the challenge to model and quantify these systems and their dynamics (Schröter et al. 2017).

1.3 Life Cycle Assessment

Worldwide efforts to protect our natural environment have led to the development of different tools and environmental impact methods that allows us to estimate at different degrees, the direct and indirect effects of human activities. With most of the current production and trading systems operating with stakeholders located all around the world, this increasing trend highlights the need for methods that can operate with a global and systems level perspective. While several methods exist to trace material-flows linked to economic activities per country, such as material flow analysis (MFA) and environmental economic input output analysis (EEIOA), the method used worldwide to compare environmental impacts of product systems is known as Life Cycle Assessment (LCA). LCA has become an internationally standardized method that allows to estimate the environmental interventions throughout the life cycle of a product or service and translates them into potential impacts (ISO 2006). LCA is used across several sectors, to provide insights for decision making aiming at more sustainable consumption and production systems (O'Shea, Golden, and Olander 2013).

LCA studies can help determine and compare the environmental implications of systems that can range from technological advances to conventional practices looking to improve their environmental performance, and are increasingly being required by legislative bodies in the EU to be presented as part of the environmental profile for new products (European Commission 2021). Furthermore, the results can help identify 'hotspots' within a studied system (i.e., processes that contribute the most to a set of environmental impacts), providing opportunities to address polluting or highly impactful activities, as well as to compare and select alternatives that present a relatively better environmental performance (Heijungs et al. 2019; Mendoza Beltran et al. 2018). These advantages along with its systems thinking approach, has made LCA a valuable method in the transition towards sustainable practices.

As a direct result of its increased use worldwide, LCA has been the subject of intense and constant research over the last decade (Bare 2011; Curran et al. 2016; Koellner et al. 2013; Mutel et al. 2019; Nordborg et al. 2017; Yi, Kurisu, and Hanaki 2014). Although its framework has been standardized, the operationalization of LCA is constantly evolving along with the capacity of LCA software and the improvement of the LCI databases and impact methods used to estimate environmental impacts (O'Shea et al. 2013). This constant development is driven by the need to improve our understanding of environmental dynamics, as well as the reach and interpretation of LCA results to support decision-making.

1.3.1 Brief overview of the framework

The current LCA framework, as standardized by the ISO 14040 and ISO 14044 (ISO 2006a,b), is an environmental analysis that comprises four main phases (Figure 1.2): i) the goal and scope definition, in which the purpose of the study and the basis for comparison, i.e. the functional unit, are specified along with the system boundaries; ii) the inventory analysis, in which all processes needed to fulfill the functional unit and their inputs and outputs are determined along with the total emissions and resources associated with the product system(s) are compiled for each alternative; iii) the impact assessment, in which the resources and emissions are translated into environmental impacts, additional measures such as weighting or normalization can take place in this phase; and iv) the interpretation step, in which the robustness and completeness of the results can be analyzed, as well as measures of uncertainty and sensitivity analyses to help in the interpretation of results.

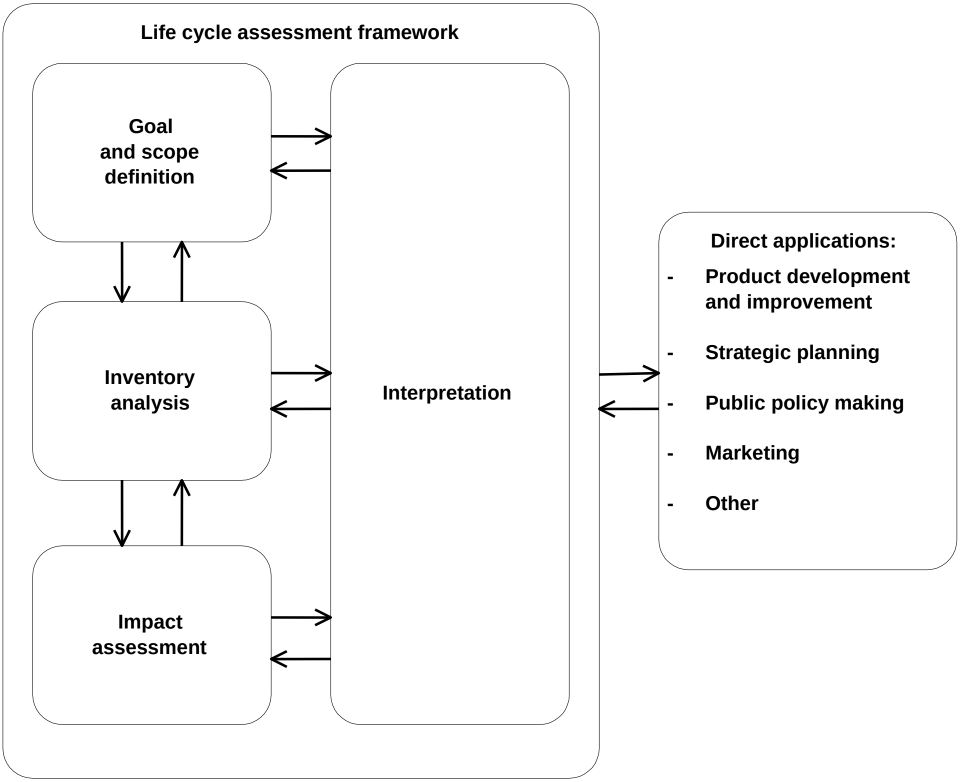

Figure 1.2 *The life cycle assessment framework. (ISO 2006)*

LCA studies consists of iterative rounds in which the goal and scope are constantly revisited, for example, to determine which processes are considered within system boundaries and to select the appropriate allocation methods to solve multifunctional processes (Guinée et al. 2002). Once the goal and scope have been determined, the inventory analysis takes place. ISO defines the inventory analysis (LCI) as the “phase of life cycle assessment involving the compilation and quantification of inputs and outputs for a product throughout its life cycle”. To do this, quantitative data is compiled for each unit process relevant to the system assessed and within the selected system boundaries. According to ISO, a unit process is the “smallest element considered in the life cycle inventory analysis for which input, and output data are quantified”. To compile life cycle inventory data, studies rely most of the times on third-party databases in an attempt to create a complete overview of the processes involved. An example of a widely used LCI database is ecoinvent, which contains information on over 18,000 activities related to diverse manufacturing practices, construction processes, energy systems, food production, transportation, among many other categories, covering globally generic and country specific scopes (Althaus et al. 2007; Wernet et al. 2016).

The LCI results contains information regarding all the elementary flows (i.e., environmental flows that correspond to resource inputs and emissions) associated with a functional unit. Thus, the relative output of each unit process is scaled for a whole system based on the functional unit defined. To further elaborate on this, we follow the standard computational nomenclature of the LCA matrix (Heijungs and Suh 2002):

$$\mathbf{A}\mathbf{s} = \mathbf{f}$$

and

$$\mathbf{s} = \mathbf{A}^{-1}\,\mathbf{f}$$

Where $\mathbf{A}$ is the technology matrix representing the flows within the economic system (with $\mathbf{A}^{-1}$ as its inverse), $\mathbf{f}$ is the final demand vector (which represents the reference flow of the system, i.e., the amount of product needed per functional unit) and $\mathbf{s}$ correspond to the scaling vector, which allows to determine vector $\mathbf{g}$, that relates the environmental flows and the economic system to its final demand, expressed as:

$$\mathbf{g} = \mathbf{B}\mathbf{s}$$

where $\mathbf{B}$ is the intervention matrix representing the environmental flows of all unit processes associated with a product system (Heijungs and Suh 2002). The expression to calculate the final inventory results, aggregated over the entire product system and across a life cycle, is the following:

$$\mathbf{g} = (\mathbf{B}\mathbf{A}^{-1})\,\mathbf{f}$$

where the inventory may be solved for a variety of final demands $\mathbf{f}$ (Heijungs and Suh 2002). Following the inventory analysis, the impact assessment phase takes place, which is aimed at “understanding and evaluating the magnitude and significance of the potential environmental impacts for a product system”(ISO 2006). To do this, the LCI results (i.e., the inventory of emissions and resources compiled for each system and scaled per functional unit) are usually converted into potential impacts by an impact characterization step:

$$h = Qg$$

where **h** is the impact vector, and **Q** is the matrix of characterization factors (CFs). This linear expression represents the contribution of **g** to a given impact category (Heijungs and Suh 2002). More recent studies are targeting the development of non-linear approaches to introduce more complex dynamics within the common LCIA framework (Arbault et al. 2014; Li et al. 2020; Pizzol et al. 2020). As addressed in Heijungs and Suh (2022): "the matrix-based approach should be regarded as a convenient and simplified approach, which is subject to further innovation and added complexity as necessary". Although non-linear and dynamic approaches present promising though also challenging avenues for future research, they remain a minority in current LCIA literature and limited to niche applications in LCA studies. Therefore, this thesis will focus for now on the common linear use of characterization factors (Heijungs 2020).

1.3.2 Characterization factors, what are they?

As previously mentioned, characterization factors (CFs) are used to convert the LCI results into indicator results. CFs are numerical values derived from characterization models that quantify the potential effect of environmental interventions to a certain impact category (e.g., climate change, eutrophication). The CFs are usually provided by developers in the form of an ordered list of data (or a spatially explicit map), specific to the LCI results assigned to impact categories in the classification step (Heijungs and Suh 2002). They are typically derived from models that take into account the environmental fate and effects of a substance, emission or resource use. To provide a brief example, to calculate the global warming result of a product system, the relevant LCI data of the system would be multiplied by the corresponding characterization factors for each greenhouse gas emitted (the so-called global warming potentials or GWPs), such as carbon dioxide, methane, and nitrous oxide. The resulting values would be summed to obtain a single value for the impact category of climate change.

Overall, characterization factors play a critical role in enabling the comparison of the potential environmental impacts that can help inform decision-making towards more sustainable options. CFs for LCA studies can be found for either one of two types, firstly for ‘midpoints’, where the characterized impact lies somewhere along the ecological cause-effect pathway, or secondly, for ‘endpoints’, where damages linked to at least one of the three areas of protection is assessed (i.e., human health, ecosystem quality and resource scarcity) (See Figure 1.3). The selection between midpoint or endpoints to compare between product systems will largely depend on the purpose of the study and the preference of the LCA practitioner. While the midpoint approach usually involves less debatable assumptions and targets ecological effects, the end-point approach can involve higher uncertainties but provides more ‘intuitive’ metrics that can be more easily interpreted for decision making (Guinée and Heijungs 2017). However, both levels of characterization can complement each other and provide information regarding the ecological effects of the studied system and their influence on human health and environmental quality (Hacikamiloglu 2007).

CFs are usually compiled in families of impact assessment methods such as Recipe2016 (Huijbregts et al. 2016) and IMPACT world+ (Bulle et al. 2019), some of which present both midpoint and endpoint CFs, with a baseline covering approximately 17 midpoint categories, and endpoints that link to at least one of the 3 AoP: human health, natural environment, and natural resources (See Figure 1.3).

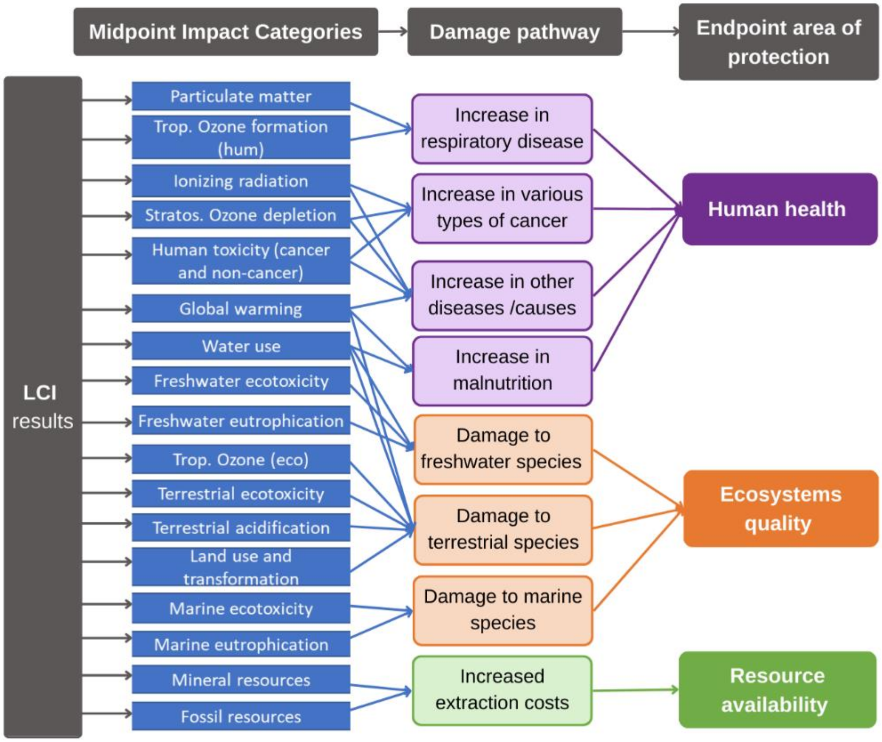

Figure 1.3 *Example of impact categories from ReCiPe2016* (Huijbregts et al. 2016). *During the impact assessment phase of LCA, LCI results are translated into midpoint impact indicator results, and through endpoints linked to at least one of the Areas of Protection.*

1.4 Assessing ecosystem service impacts in LCA

Until this past decade, the explicit mention of ecosystem services was completely missing from the LCA literature. This changed after the first review published by Zhang et al. (2009), who presented an overview of the possibilities for integrating the concept of ecosystem services in LCA studies (Zhang, Sing, and Bakshi 2010; Zhang, Singh, and Bakshi 2009). Since then, several authors have proposed different recommendations, some analyzing the opportunities from a conceptual approach (Bakshi and Small 2011; Dewulf et al. 2015; Maia de Souza et al. 2018; Rugani et al. 2019; Xinyu, Ziv, and Bakshi 2018), while others have worked on methods that can combine in some cases economic data (Cao et al. 2015) as well as emergy and exergy values (Rugani et al. 2013). Furthermore, several studies have tried to tackle the spatial variation aspects that influence ecosystem services, especially those related to land use (Arbault et al. 2014; Chaplin-Kramer et al. 2017; Karabulut et al. 2016). Unfortunately, a lot of these approaches are limited in applicability, sometimes due to the fact that they deviate significantly from the LCA framework or common LCA practices, which can ultimately hinder a wide implementation of the methods proposed.

Aiming for the assessment of ecosystem services within common LCA practices, another approach has been followed by studies that focused on the development of characterization factors that can be used in the impact assessment phase of LCA (Brandão and I Canals 2013; Saad, Koellner, and Margni 2013; Schmidt 2008; Seppälä et al. 2006). Addressing the impact assessment phase, Othoniel et al. (2016) presented a comprehensive overview of the challenges of incorporating the explicit assessment of ecosystem service within LCA, and clearly explained some of the limitations encountered for the adaptability of existing methods and incompatibilities of jargon that can lead to divergent views on ecosystem service analysis and interpretation.

The debate around jargon incompatibilities seems to center most of the times on whether we are assessing impacts on ecological processes linked to the supply of ecosystem services, or assessing the impacts on the supply of the benefits themselves (Othoniel et al. 2016). The first case presents more compatibilities for incorporation within common LCA practices, while the second one is challenging due to intrinsic characteristics of supply and demand functions, such as site dependency and temporal dynamics (Othoniel et al. 2019). For the first, where the impact is assessed at one point within the ecological cause-effect chain, the development of characterization factors presents valuable opportunities to incorporate new impact categories in LCA that can be directly linked to key ecosystem services (Kumar, Esen, and Yashiro 2013). International initiatives, such as the UNEP-SETAC, have proposed general guidelines and recommendations for the characterization of ecosystem services and biodiversity impacts to promote harmonized efforts (Koellner et al. 2013; Rugani et al. 2019; Verones et al. 2017). However, further research is needed to achieve an extended and successful incorporation of new impact categories that can be directly linked to ecosystem services, allowing for a more comprehensive overview of key environmental impacts (Callesen 2016) .

1.5 Problem identification

Despite the increasing evidence on the relevance of ecosystem services, their assessment in LCA studies remains limited to a handful of categories, most of them assessing indirectly, the potential impacts on identified ecosystem services. In order to increase their coverage in LCA studies, further development of impact assessment methods is needed. As mentioned in previous sections, two main challenges have been identified as hindering the development and successful implementation of new impact categories targeting ecosystem services in LCA. Both challenges are related to the compatibility with common LCI data and conventional LCIA practices. Impact assessment models targeting ecosystem services are usually complex, non-linear models that require high spatially detailed input data, while LCI data is often geographically coarse, with countries as the maximum level of geographical specificity presented for most unit processes. Reconciling both the compatibility of characterization models and characterization factors with common LCI data and LCIA practices, is of high relevance to allow for a practical implementation of the methods proposed. Although the development of characterization factors and the application of the LCA method are usually independent activities, these should not be carried out in disregard of each other, as these crucial mismatches between the specificity of the CFs and the available inventory data can limit the application of new impact categories to only a few specific LCA studies. Furthermore, there is yet no clear guidance on which ecosystem services should be targeted for incorporation in LCA studies, leading to the overarching questions: what would a comprehensive coverage of ecosystem services in LCA entail, and how can we overcome the identified challenges?

1.6 Research objectives of the thesis

This thesis extends the body of knowledge aimed at the incorporation of ecosystem service impacts in LCA studies. The objectives of this thesis are addressed in the following research questions:

RQ1: *Based on the current impact assessment methods available and the existing ecosystem services identified, what would be the optimal coverage of ecosystem services in LCA studies?*

RQ2: *To incorporate the assessment of new ecosystem services in LCA, how can we reconcile the differences that exist between ecosystem service methods, the LCA framework and available LCI data?*

RQ3: *How can we address key data gaps to produce readily applicable characterization factors for the assessment of ecosystem services in LCA?*

RQ4: *How can we increase the representation of intra-national differences that are relevant for ecosystem services, in country-specific characterization factors?*

1.7 Outline of the thesis

Following the research questions (Figure 1.4), this thesis has been organized starting with one introductory chapter (**Chapter 1**), followed by four content chapters (**Chapters 2-5**), and one concluding chapter (**Chapter 6**). In **Chapter 2**, I present an overview of the impact categories included in common impact assessment methods, identifying the ecosystem services that are directly and indirectly included. Parting from there, I compared the results with those ecosystem services included in inventories by CICES to identify the ones currently missing, and that should be the target for an optimal coverage in environmental LCA studies. From the ecosystem services identified as missing, I used available economic valuation data to provide a sense of perspective on the potential costs of neglecting their assessment and protection.

In **Chapter 3**, I tackled one of the key ecosystem services identified as missing from commonly used impact methods, to propose an approach that can allow for the characterization of impacts in a compatible way with available LCI data.

A review of impact assessment models from diverse disciplines targeting the selected ecosystem services was conducted in order to determine, from those available, which ones could be applicable for LCA and propose the required adaptations. The impact assessment model proposed is illustrated first with exemplary characterization factors produced in conjunction with an expert from the field of the ecosystem services studied.

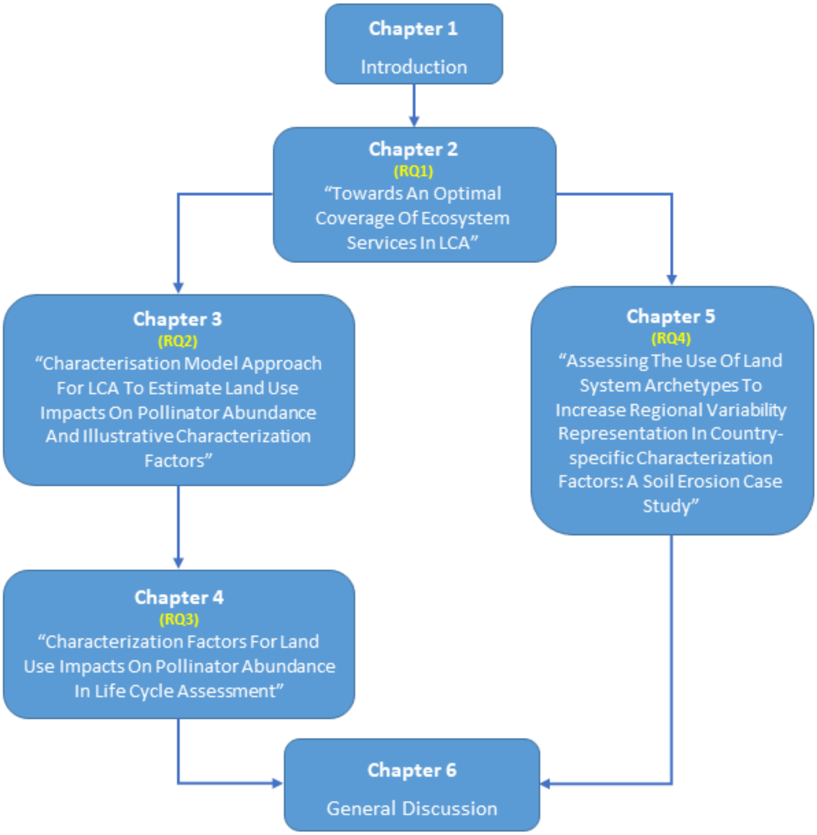

Figure 1.4 *Outline of this thesis.*

To move from illustrative to readily applicable characterization factors, I present in **Chapter 4** the procedure and results of an interdisciplinary collaboration with 25 expert researchers from around the world, that resulted in the derivation of the first set of characterization factors that allows to translate land use impacts on wild pollinators. Through the use of an expert elicitation method, I retrieved representative data pertaining to the field of the ecosystem service studied, by presenting a useful way to fill in knowledge gaps for characterization of impacts.

Lastly, given the current limitations on geographical specificity in LCA studies and the high relevance of biogeographical differences for many ecosystem services, I explored in **Chapter 5** how to improve the representation of intranational differences when producing country-specific characterization factors. This was done by applying land system archetypes derived from clustering techniques that combine both biogeographical and socioeconomic factors, to produce CFs that can represent the high diversity of impacts associated with site-dependent ecosystem services, such as is the case for the soil erosion resistance capacity. Previous studies had produced country-specific CFs for soil erosion based solely on biogeographical parameters and using the potential natural vegetation (PNV) as a reference state. In this chapter I produced CFs using information from land system archetypes as an alternative reference state, to compare our results with previous studies and challenge common practices that could potentially hinder the representation of key intranational variations.

In **Chapter 6**, I present a general discussion highlighting the main findings, addressing the limitations of our research as well as the challenges and opportunities for future researchers looking to dive into the topic of impact characterization of ecosystem services. The outcomes of this thesis are expected to provide useful insights not only on a viable way to expand the coverage of key environmental impacts in LCA studies, but also on the importance of interdisciplinary collaboration as an essential pillar for environmental research.

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Chapter 2

Towards an Optimal Coverage of Ecosystem Services in LCA

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Abstract

Our society relies on the sustained provisioning of ecosystem services (ES), while such provisioning has been negatively affected by human activities. Recently, several authors proposed indicators for the assessment of ES in Life Cycle Assessment (LCA) studies and developed corresponding characterization factors for integration in the impact assessment phase of LCA (LCIA). However, the vast majority of these indicators are still not operational and not a single study has presented a comprehensive list of ES for inclusion in LCIA. As a result, the individual efforts to incorporate ES in LCIA lack guidance from a framework to comprehensively assess and prioritize ES for inclusion in LCIA. This study addresses the aforementioned knowledge gap, and presents an original framework for the optimal coverage of ES in LCIA. We first identify, describe and visualize ecosystem services assessed currently (directly and indirectly) included in the widely applied LCIA method ReCiPe2016. Next, we propose an optimal coverage of ES in LCIA consisting of 15 categories of ES, including provisioning, regulation and maintenance, and cultural services, derived from the ES classification method CICES V5.1. Next, we identify the gap between the current and optimal coverage, consisting of 11 ES categories currently not covered by ReCiPe2016. As a proposal to help accelerate the incorporation of missing ES, we finally prioritize missing categories using available monetary valuation data, resulting in a ranking of ES categories to be included in LCIA. The four categories that rank highest are “Regulation of flows and protection from extreme events”, “Mediations of wastes, toxics and nuisances”, “Water conditions” and “Aesthetic value”. Our analysis and prioritization can help setting a research agenda for the scientific community to collaboratively and comprehensively incorporate missing ES categories in LCIA.

Keywords: Ecosystem Services; Life Cycle Assessment; Impact Assessment.

2.1 Introduction

A key sustainability challenge of the 21st century is to assess and decrease the variety of anthropogenic impacts to the environment (Díaz et al., 2018). Human societies depend on the natural environment to obtain multiple goods and services, generally referred to as ecosystem services (ES). Ecosystem services have become a trending field of research over the past decade, with an approximate of 3000 scholarly articles published on the topic just in 2016 (McDonough et al., 2017). According to Costanza et al. (2014), the term 'ecosystem services' appeared in 1981 by Ehrlich and Ehrlich (1981), as a synonym of an older term: 'nature's services'. Both terms refer to the idea that natural systems provide benefits that support human well-being (Costanza et al., 2014).

As presented by the Millennium Ecosystem Assessment (MEA 2005), the majority of the services studied show severe degradation due to human activities. In turn, this degradation of ecosystem services poses a risk for human well-being and in order to help prevent further damages and exploitation of ES, it is necessary to assess potential impacts on them applying environmental assessment methods. One of the most widely applied environmental assessment methods is life cycle assessment (LCA). LCA is method of which the general principals and requirements have been laid down in International Organization for Standardization (ISO) series of Standards on LCA. Applying LCA, the potential environmental impacts associated with a product over its entire life cycle can be quantified (Guinée et al., 2002).

According to the ISO 14040-14044 standards (ISO 2006), the framework of an LCA follows four phases; goal and scope definition, inventory analysis, impact assessment and interpretation. LCA requires continuous improvement to deliver up-to-date results that are relevant for addressing current societal and environmental problems. An improvement proposed over the last years includes the idea of incorporating the impact assessment of ES in life cycle impact assessment (LCIA) methods. While ES are increasingly considered a key component in the relation between human society and the environment, LCA studies hardly include explicit impacts on ecosystem services. The impact categories assessed in LCA mainly consider impacts on resource availability and ecosystem quality, without explicitly considering ecosystem services. However, a wide variety of processes and conditions that are essential for the technosphere rely on ecosystem services (See Fig. 2.1).

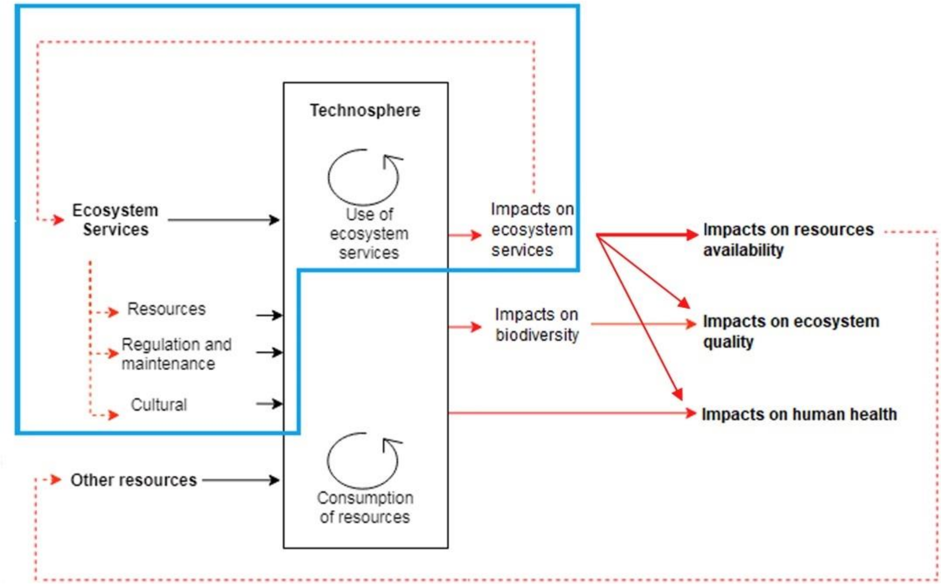


Figure 2.1. *Relations between technosphere and environment. Ecosystem services are inputs (black arrows) to the technosphere, along with other resources that do not classify strictly as ecosystem services (e.g., soil, chemicals, etc.). The impacts from the technosphere (red arrows) have effects on ecosystem services, of which some are directly linked with the three main areas of protection used in LCA, resource availability, ecosystem quality and human health. Impacts on ecosystem services have negative feedback on the technosphere that consumes and benefits from these services. This study focuses on the assessment of ecosystem services, which is shown by the blue box that excludes biodiversity and impacts to other aspect such as human health.*

Thus, it is necessary to more comprehensively and explicitly include ES in LCA to achieve a better coverage of key environmental impacts that are associated with a product system. In the past years, several studies have focused on the topic of ecosystem services in LCA. Some authors have worked on modelling characterization factors for LCIA to assess impacts of land use on ES, such as impacts on biotic production (Brandao and I Canals 2013; Saad et al. 2013), freshwater regulation, water purification and erosion regulation (Beck et al. 2010; Cao et al. 2015; Saad et al. 2013). Global characterization factors and guidelines have been published for assessing ES in LCA (Koellner et al. 2013; Koellner and Geyer 2013) and the limitations and challenges for such integration have been extensively described in the literature (Othoniel et al. 2015; Tang et al. 2018; Zhang et al. 2010).

Furthermore, several approaches have been proposed for the explicit assessment of ES within LCIA, each with very different methods and considerations, such as the use of provisioning rates as characterization factors for ES (Blanco et al. 2017), the incorporation of socioeconomic aspects of ES to calculate an aggregated endpoint (Cao et al. 2015) or the evaluation of environmental externalities (Bruel et al. 2016), as well as frameworks assessing techno-ecological synergies that could be considered in parallel to or complementing LCA (Xinyu et al. 2018). However, there is no framework in the literature pointing at which selection of ecosystem services would comprise an optimal coverage in LCA. Drafting such a framework demands an appropriate integration of knowledge from both the ecosystem services and the LCA community to determine relevant ES categories for inclusion in LCA.

This paper aims to bring together knowledge from both communities in order to define an optimal coverage of ES in LCA, and therefore, evaluate and recommend which ecosystem services categories form such optimal state. Optimal coverage of ES in LCA is defined here as the 'inclusion of a minimum number of ES categories that still sufficiently represents the wide variety of specific ES'. To achieve this, we first determine which ES are already covered by a state-of-the-art LCIA method, which ES have been proposed to add to LCA by other authors, and which ES are distinguished by the ES scientific community. Subsequently, we derive the ideal level of ES inclusion in LCA by presenting an optimal coverage composed of multiple ES categories derived from internationally accepted classification systems. Finally, we conduct a prioritization analysis among ES according to their monetary values as an approach to guide efforts and accelerate their inclusion in LCA.

2.2 Methods

The research steps adopted for defining an optimal coverage of ES in LCA are summarized in Figure 2.2. The first step consists of determining the 'current' state of ES in LCA. The current state was composed by preparing an overview of which ES are already covered by LCIA methods and which ES have been proposed for addition in LCA. We selected an LCIA and an ES classification method on which we based our analysis. To complete our analysis, we conducted a bibliometric analysis was carried out of the ISI Web of Science (WoS) published by Thomson Reuters on efforts made so far by other authors proposing concrete indicators for ES in LCA. The keywords used were 'Life Cycle Assessment' AND 'Ecosystem Services' (accessed on 16/02/2018). Only those articles that proposed specific indicators for the assessment of ES in LCIA were taken into account.

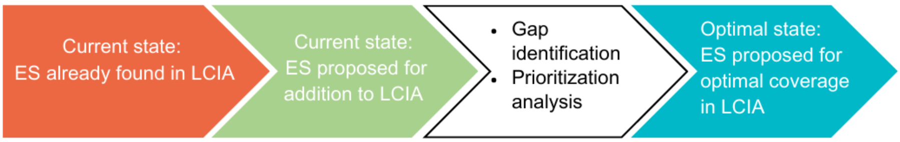


Figure 2.2 *Steps of the research.*

From the literature search we obtained a list of 274 articles, from which 34 contained information about LCA and ecosystem services. We further selected only those studies that contained information specifically about the implementation of ecosystem services in LCA and that propose concrete indicators for their evaluation in LCA. Articles proposing indicators to assess ES in LCA based on emergy (e.g., Rugani et al. 2013) and hemeroby (e.g., Fehrenbach et al. 2015) were also excluded also because of their incompatibility with current practices and limited focus on the impacts on ES. The next step was deriving an optimal coverage based on a representative ES classification method. Based on a comparison of results from the 'optimal' and 'current' coverage, we assessed which indicators are already proposed in the LCA-ES literature for complementing the current coverage of ES in impact assessment methods. The last step consisted of a prioritization exercise in which ES from the optimal state currently missing in LCIA methods were ranked based on available information, in this case, monetary values.

2.2.1 Selection of ES terminology and classification system

Since the introduction of the term 'ecosystem services', a multitude of definitions and classification systems for ecosystem services has arisen. This has caused a wide variety of interpretations on what exactly are ecosystem services, with different classification systems existing such as the 'Common International Classification of Ecosystem Services' (CICES), the 'Final ecosystem goods and services classification system'(FEGS-CS), the 'National ecosystem services classification system' (NES-CS), and the ones used by The Economics of Ecosystems and Biodiversity (TEEB), and the Millennium Ecosystem Assessment (MEA). For this study, the classification system for ES selected was CICES V5.1 (Haines-Young and Potschin 2018), since it is widely used and vastly accepted by policy makers.

In contrast to other ES classifications, such as the one used by the Millennium Ecosystem Assessment and the TEEB, CICES also accounts for abiotic resources as provisioning services, which are an important element of LCA inventories and crucial for the assessment of the impact category "abiotic resource depletion". CICES is also an international classification, unlike the FEGS-CS and NES-CS which are focused and developed by the United States government. CICES distributes ecosystem services into three categories: provisioning, regulating and maintenance, and cultural services. However, this classification scheme does not provide a clear distinction between services and benefits.

To avoid misunderstandings, we will refer to ecosystem services as the service provided by ecological functions and processes that contribute to human well-being (La Notte et al. 2017), and benefits as the perceived value for humans of such services. In order to use the CICES classification within the framework of LCA we will adapt the terminology used by CICES to better reflect the difference between service and benefits in the classification and categorization of our results. This study focuses exclusively on ecosystem services. Since biodiversity is not an ecosystem service itself, it is left out of the scope of this study. The link between species and ecosystem services depends on the functional relevance of the species. This means, the importance of species depends on their service to the technosphere (for example, do they serve as materials or do they serve other purposes that contribute to human well-being). Therefore, we can only take particular species into account as ecosystem services if we know that those species are being used for a certain purpose. If the functional relevance cannot be determined, as is the case with the "Disappeared fraction of species" indicator used in LCA, for which we do not know the exact species considered, we cannot link it to an ecosystem service. It should still be included in LCA as a biodiversity impact, but it is out of the scope of this study.

2.2.2 Selection of the LCIA method

There is a wide variety of LCIA methods, some containing only midpoint indicators such as the CML impact assessment method (Guinée et al. 2002), some others focusing on end-points only as the Eco-indicator 99 (Goedkoop and Spriensma 2000), and some with both midpoint and endpoints as for example the methods LC-Impact (Verones et al. 2016), Impact World (Bulle et al. 2019) and ReCiPe (Huijbregts et al. 2016). We selected the most recently updated method with the broadest set of indicators, in this case ReCiPe2016. ReCiPe is an acronym that represents the initials of the institutes that were the main contributors and collaborators in its design: RIVM and Radboud University, CML, and PRé Consultants. ReCiPe2016 contains 17 midpoint categories and 3 endpoint categories (Huijbregts et al. 2016). For this study we use ReCiPe2016 to analyze in depth its impact categories and determine if (and which) ES are accounted for within these categories. For the impact categories climate change and toxicity, external models had to be consulted for further clarification on the aspects involved in their characterization factors. Climate change relies on the characterization factor "Global Warming Potential" (GWP), which is provided by the IPCC (2006). The characterization factors for toxicity in ReCiPe2016 are based on the USES-LCA model (Van Zelm et al. 2009).

2.2.3 Prioritization of ES

Based on the inventory of ES categories constituting the optimal state in LCAs, a prioritization was made to steer and accelerate research for assessing and incorporating ES in LCA. Ideally, such prioritization would use indications of their value, degree of impact or degradation, and regeneration time. However, the only databases available evaluating and comparing ES of diverse categories across the globe are based on monetary valuation (de Groot et al. 2012; Van der Ploeg et al. 2010). Despite its limitations (Schild et al. 2017; Silvertown 2015), monetary valuation can help prioritize among the ES categories proposed for the optimal coverage, and the ES within the proposed categories. Based on the estimated monetary valuation of ES as presented by de Groot et al. (2012) we ranked categories of ES that have not been incorporated in ReCiPe2016, and (if possible) the ecosystem services within those categories. In order to rank the ES categories by monetary value, we matched the ES categories used and evaluated by de Groot et al. (2013) with our proposed ES categories (See Supporting information for detailed procedure).

2.3 Results

2.3.1 Current coverage of ES in LCA

2.3.1.1 Ecosystem services already covered in ReCiPe2016

We found that five mid-point impact categories of ReCiPe2016 are linked with specific ecosystem services (see Fig. 2.3):

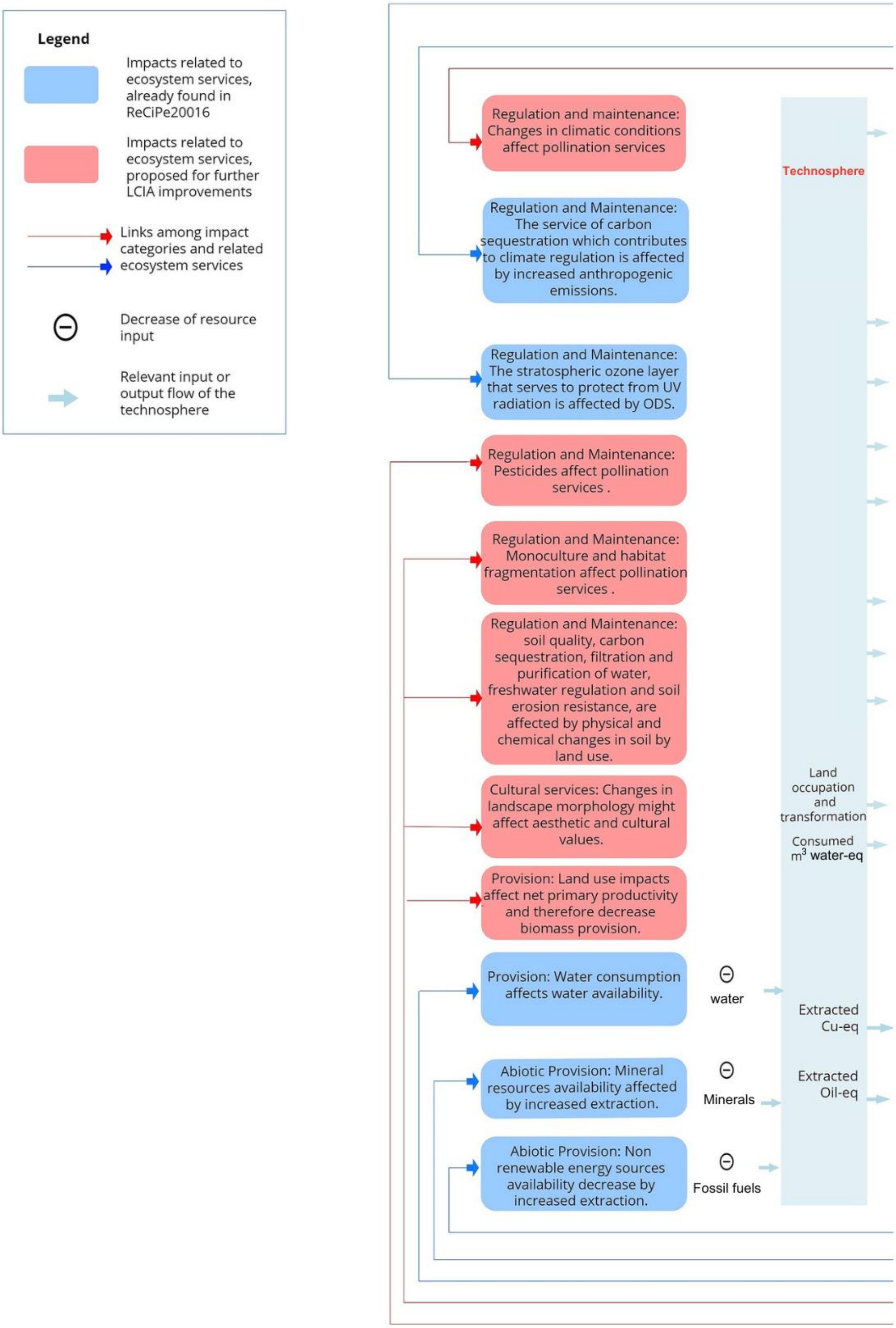
- The category of climate change is related to regulation and maintenance services. Within this category, carbon sequestration -which is a service that contributes to climate regulation- is taken into account in the characterization model of the IPCC and thus also in the characterization factor GWP. Carbon sequestration and its effects on climate regulation are affected by increased anthropogenic emissions. This dynamic is modelled as part of the GWP.

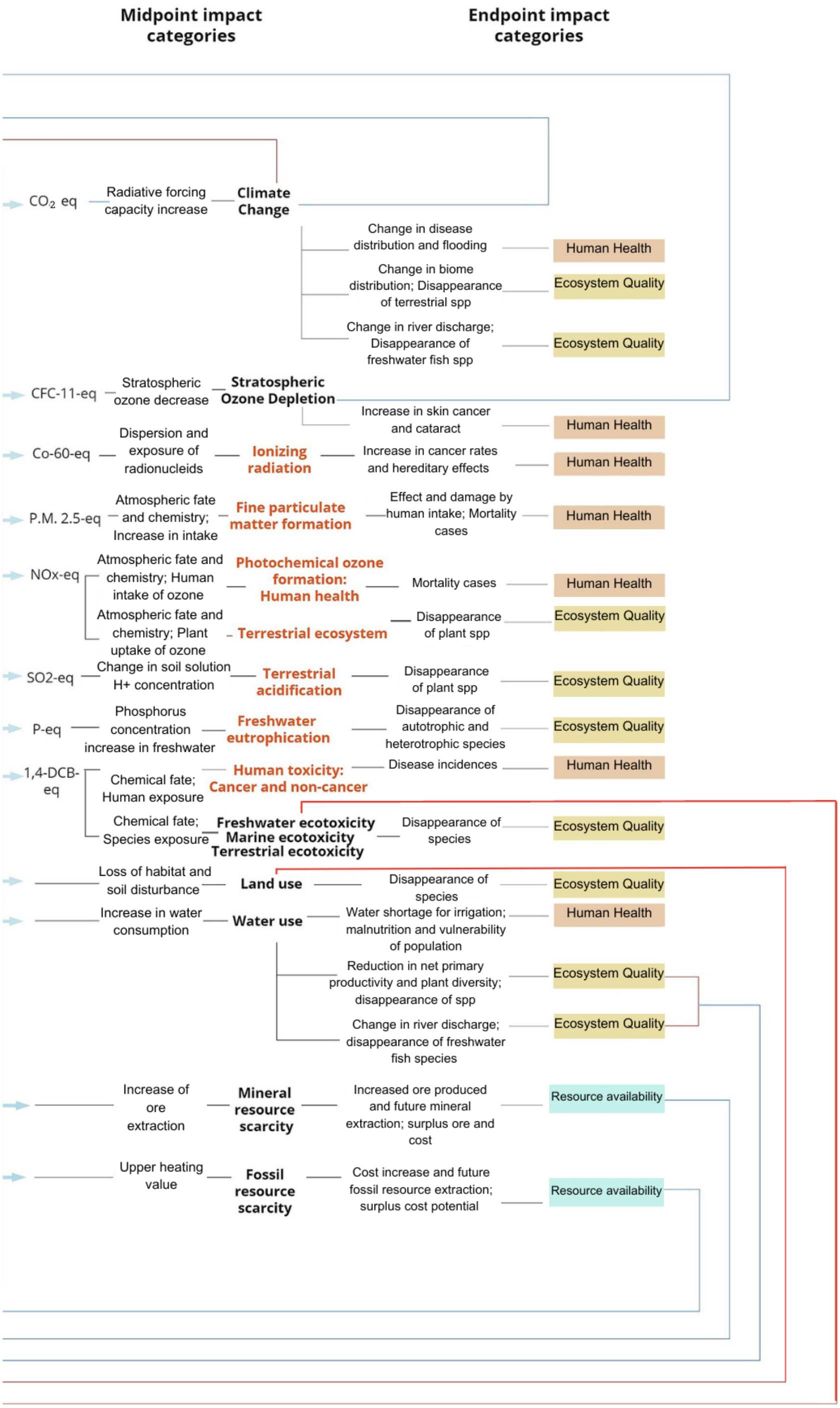
- The stratospheric ozone depletion category is also directly linked with regulation and maintenance services. The stratospheric ozone layer serves as protection against UV radiation and can be considered an ecosystem service itself.
- The category of water use refers to both fresh and groundwater availability. This category can be seen as the ecosystem service of water provisioning.
- Mineral resource scarcity and Fossil resource scarcity correspond directly to the ecosystem services of mineral and non-mineral resources provisioning, where increased extraction decreases the availability of the corresponding resources.

For the remaining impact categories, the relation with specific ecosystem services was either not found, or considered to be too uncertain and indirect. Next to "disappeared fraction of species", major uncertainties apply to ionizing radiation, where it could be argued that DNA damage through radionuclides exposure can cause cancer and hereditary effects, affecting the provisioning of biomass and genetic resources. Photochemical ozone formation also has negative effects on biomass, reducing net primary productivity. Until the relationships with ES are further clarified, these categories cannot be considered as impacting on ES.

Figure 2.3 (In page 38-39) *Relations between existent impact categories and ecosystem services. (For high resolution: https://ars.els-cdn.com/content/image/1-s2.0-S0959652619318207-gr3_lrg.jpg)* ›

Link with ecosystem services




Midpoint impact categories
Endpoint impact categories
CO2 eq
Radiative forcing capacity increase
Climate Change
Change in disease distribution and flooding
Human Health
Change in biome distribution; Disappearance of terrestrial spp
Ecosystem Quality
Change in river discharge; Disappearance of freshwater fish spp
Ecosystem Quality
CFC-11-eq
Stratospheric ozone decrease
Stratospheric Ozone Depletion
Increase in skin cancer and cataract
Human Health
Co-60-eq
Dispersion and exposure of radionucleids
Ionizing radiation
Increase in cancer rates and hereditary effects
Human Health
P.M. 2.5-eq
Atmospheric fate and chemistry; Increase in intake
Fine particulate matter formation
Effect and damage by human intake; Mortality cases
Human Health
NOx-eq
Atmospheric fate and chemistry; Human intake of ozone
Photochemical ozone formation: Human health
Mortality cases
Human Health
Atmospheric fate and chemistry; Plant uptake of ozone
Terrestrial ecosystem
Disappearance of plant spp
Ecosystem Quality
SO2-eq
Change in soil solution H+ concentration
Terrestrial acidification
Disappearance of plant spp
Ecosystem Quality
P-eq
Phosphorus concentration increase in freshwater
Freshwater eutrophication
Disappearance of autotrophic and heterotrophic species
Ecosystem Quality
1,4-DCB-eq
Chemical fate; Human exposure
Human toxicity: Cancer and non-cancer
Disease incidences
Human Health
Chemical fate; Species exposure
Freshwater ecotoxicity
Marine ecotoxicity
Terrestrial ecotoxicity
Disappearance of species
Ecosystem Quality
Loss of habitat and soil disturbance
Land use
Disappearance of species
Ecosystem Quality
Increase in water consumption
Water use
Water shortage for irrigation; malnutrition and vulnerability of population
Human Health
Reduction in net primary productivity and plant diversity; disappearance of spp
Ecosystem Quality
Change in river discharge; disappearance of freshwater fish species
Ecosystem Quality
Increase of ore extraction
Mineral resource scarcity
Increased ore produced and future mineral extraction; surplus ore and cost
Resource availability
Upper heating value
Fossil resource scarcity
Cost increase and future fossil resource extraction; surplus cost potential
Resource availability

2.3.1.2 Ecosystem services proposed for inclusion in LCA currently found in the literature

The publications eventually selected for describing the current coverage of ES in LCA are listed in the Supporting information. Most indicators proposed focus on land use impacts (Beck et al. 2010; Cao et al. 2015; Mila i Canals et al. 2007a; Núñez et al. 2013) and their effects on regulation and maintenance services (see Fig. 2.3). Only one article was found proposing to include a cultural service indicator into LCA (Burkhard et al. 2012; Vidal Legaz et al. 2017).

2.3.2 An optimal coverage of ES

Based on the complete list and description of CICES V5.1 classification, we summarized the data and obtained a total of 31 ecosystem services groups (see Table 2.1). Four groups were considered as non-pertinent for LCA, these are cultural services that are assessed through societal aspects and would be more suitable for social LCAs instead of environmental LCAs (the topic of this study). Only ecosystem services that are targeted or assessed through an ecological function or process are considered as pertinent for environmental LCAs. Once the non-pertinent groups had been removed, we summarized and derived categories from the remaining groups (see detailed explanation in Supporting information). For example, the category "Biomass provision" is derived from the CICES groups regarding biomass, including cultivated and wild plants and animals, both aquatic and terrestrial.

At the end, we obtained 15 categories that form the optimal coverage of ecosystem services. From those 15 categories, only four are covered (some partially) in ReCiPe2016. This is the case for 1) "water provisioning", covered by the water use impact category. 2) "Atmospheric composition and conditions regulation" can be linked to both climate change impact category and stratospheric ozone depletion. 3) "Mineral resources" are directly assessed in the mineral resource scarcity impact category, and 4) "Non-mineral resources" in the fossil resource scarcity impact category. The remaining 11 categories of our optimal state proposed are still entirely lacking in LCAs. However, several of these can be covered by LCIA methods if the indicators proposed and presented in the previous section become operational (although we are not endorsing any of the methods or indicators proposed, but merely describing the advantages from the point of view of ES coverage). In the end, 4 out of the 15 categories proposed have neither been included nor proposed as indicators for their inclusion in the impact assessment method of LCA. These 4 categories correspond to “Genetic material resources”, “Mediation of smell, noise and visual impacts”, “Pest and disease control”, and “Maintenance of abiotic conditions”.

Table 2.1 *Deriving the optimal state for coverage of ES in LCAs. Categories that are already accounted for in ReCiPe2016 are listed in italic, categories for which indicators have already been proposed in the literature are followed by an asterisk (*).*

Classification by CICES V5.1	ES groups by CICES V5.1	Proposed ES categories for optimal state
Provision (biotic and abiotic)	Cultivated terrestrial and aquatic plants for nutrition, materials or energy Reared terrestrial and aquatic animals for nutrition, materials or energy Wild animals (terrestrial and aquatic) for nutrition, materials or energy Wild plants (terrestrial and aquatic) for nutrition, materials or energy	1. Biomass provision *
	Genetic material from animal, plants, algae or fungi and other organisms	2. Genetic material resources
	Mineral substances used for nutrition, materials or energy	3. *Mineral resources*
	Non-mineral substances or ecosystem properties used for nutrition, materials or energy	4. *Non-mineral resources*
	Surface water used for nutrition, materials or energy Ground water for used for nutrition, materials or energy	5. *Water provision*
Regulation & Maintenance (Biotic and abiotic)	Mediation of wastes or toxic substances of anthropogenic origin by living and non-living processes	6. Mediation of wastes, toxics and nuisances (Filtration, sequestration, storage) *
	Mediation of nuisances of anthropogenic and non-anthropogenic origin	7. Mediation of smell/noise/ visual impacts
	Regulation of baseline flows and extreme events	8. Regulation of flows and protection of extreme events *
	Lifecycle maintenance, habitat and gene pool protection	9. Habitat and gene pool maintenance *
	Pest and disease control	10. Pest and disease control
	Regulation of soil quality	11. Soil quality *
	Water conditions	12. Water conditions *
	Atmospheric composition and conditions	13. *Atmospheric composition and conditions regulation*
	Maintenance of physical, chemical, abiotic conditions	14. Maintenance of abiotic conditions

2.3.3 Prioritizing ES for incorporation in LCAs

Based on the estimated monetary valuation of ES as presented by de Groot et al. (2012) we first ranked the eleven remaining categories of ES that have not been incorporated in ReCiPe2016, and secondly, the ecosystem services within the eleven categories of ES. For this purpose, we first allocated each of the 22 types of ES used in the study by de Groot et al. (2012) to the ES categories proposed for an optimal coverage by this study (presented in Table 2.1). For example, the categories food, medicinal resources, raw material and ornamental resources used in de Groot et al. (2012) were grouped under the category "Biomass provision". The total estimated monetary value of ecosystem services across biomes was calculated per category by summing the monetary value of each of the ES considered within a category (Table 2.2). The ES category with highest priority for inclusion in LCA was "Regulation of flows and protection from extreme events" (Table 2.2). Within this category, the most valuable ES corresponds to erosion prevention, followed by disturbance moderation. The category "Mediation of wastes, toxics and nuisances" and "Water conditions" were placed together as the second highest valuable (waste treatment and water purification are grouped together in the TEEB classification used by de Groot et al. (2012)). The "Aesthetic value" category, ranking as the third most valuable, represents cultural services such as aesthetic information, recreation and cognitive development, with recreation being the most valuable ES type within this category.

Table 2.2 *Ranking of categories of the optimal state missing from ReCiPe2016 based on economic valuation estimates.*

Rank #	ES categories proposed for optimal state	ES used by de Groot et al. (2012)	Monetary value (int.$/ha/year, 2007 price levels)
1	Regulation of flows and protection of extreme events	Erosion prevention	185,195
		Disturbance moderation	25,394
		Regulation of water flows	5,948
2	Mediation of wastes, toxics nuisances / Water conditions	Waste treatment	165,500
3	Aesthetic value	Recreation	105,336
		Aesthetic information	12,849
		Cognitive development	1,168
4	Habitat and gene pool maintenance	Genetic diversity	26,155
		Nursery service	13,418
		Pollination	61
5	Genetic material resources	Genetic resources	33,071
6	Biomass provision	Raw materials	22,819
		Food	6,728
		Medicinal resources	1,905
		Ornamental resources	618
7	Soil quality	Nutrient cycling	1,854
8	Pest and disease control	Biological control	1,194
-	Mediation of smell, noise and visual impacts	NA	NA
-	Maintenance of abiotic conditions	NA	NA

2.4 Discussion

This study presents a list of 15 ES categories that should be considered in LCA and that together could constitute an optimal state for ES coverage (Table 2.1). This optimal state can be used as guidance for future research to provide characterization factors for those ES that still need to be included in LCA. By providing an optimal state, and therefore an indication or reference point of ES that we should focus on, we can help accelerate the incorporation of a more complete coverage of relevant impacts while minimizing overlap and avoiding double-counting. At the same time, the list of categories provided in this study helps shedding a light on the increasing number of indicators needed for incorporation in LCA. If we consider all categories that could be included in LCA regarding ES, the impact assessment of LCA would easily consist of at least 27 midpoint impact categories in total. While some efforts have focused on trying to find common ground among existent categories to minimize the amount of impact categories needed in the impact assessment of LCA (Steinmann et al. 2017), it is also arguable that the impact assessment of LCA is still considerably limited, and the addition of impact categories assessing a wide range of impacts is essential to improve its robustness. A major complication is that this increased number of impact categories complicates the interpretation and decision making based on LCA results. This issue will have to be addressed in future research studying how to help practitioners deal with an increased number of indicators while facilitating their selection and interpretation for decision making processes.

2.4.1 Robustness of the optimal state

The optimal state proposed in this study comprises 15 ES categories that were derived from the internationally accepted ES classification method CICES. These categories and their subsequent prioritization may have been influenced by the choice of impact assessment and classification methods that were used to assess the current state of ES in LCA and to derive the optimal state proposed. If instead of using ReCiPe2016 to assess the current state we had chosen another impact assessment method (e.g., LC-Impact, Impact World+, etc.), we would have found a different number of ecosystem services considered (e.g., non-mineral resources would not consistently have been considered, for instance the

LC-Impact method does not assess fossil resource scarcity), resulting in a larger or smaller gap between the current and optimal state. On the same note, if another ecosystem services classification system had been used, the proposed categories might have differed slightly (e.g., the Millennium Ecosystem Assessment has limited the concept of natural capital to ‘life on Earth’ and therefore excludes abiotic resources such as mineral resources (Lele et al. 2013; MEA 2005)). CICES does account for mineral resources as a provisioning service and is therefore one of our proposed categories for the optimal state. To improve the robustness of an optimal state, the analysis could be repeated using different classification systems or by using a harmonized classification system. However, since most classification systems differ only slightly in what they consider a service or a benefit, and in how they categorize and aggregate ES types, we think the differences would be only minor.

2.4.2 Prioritization results and robustness

To help bridging the gap between the current and optimal state we conducted a prioritization analysis. The results of this prioritization can be used to make fast steps forward in the inclusion of ES in LCA. The results of this analysis indicated that ecosystem services related to regulation of flows and protection of extreme events ranked as the highest priority. Ecosystem services that provide mediation of wastes/water conditions and aesthetic value were ranked as second and third in the prioritization ranking, respectively.

Two aspects should be considered when examining the results obtained from this analysis. First, the robustness of the monetary values used from de Groot et al. (2012) should be considered. The estimated values of global averages of ecosystem services per ha can vary across time depending on the changes in the average functionality of ecosystem service per ha and the possible changes in environmental and social capital (Costanza et al. 2014; de Groot et al. 2012). Furthermore, the estimates of monetary values of ES are highly dependent on the valuation methods used, the socio-economic context of the studied ES and even the type of values used (e.g., market value, present value, etc.). For example, Costanza et al. (2014) compared global average values of ecosystem services from an earlier study by Costanza et al. (1997) with those published by de Groot et al. (2012). The values obtained for de Groot et al. (2012) appeared to be approximately eight times higher than those obtained for Costanza et al. (1997). One of the main reasons for this difference was the increased number of valuation studies that had become available, in combination with a different suite of valuation techniques applied. The monetary values used by de Groot et al. (2012) were last updated in 2011 and we can assume with high certainty that the monetary values of ecosystem services have changed from 2011 to present, due to the fast degradation caused by anthropogenic activities. The use of updated unit values would therefore lead to different global average estimates per ha and potentially also to different prioritization ranking results if degradation has affected services differently. Moreover, monetary valuation may be more appropriate for e.g., provisioning services than for cultural services, causing an underestimate of e.g., cultural services (Schild et al. 2017). Also, not all ecosystem services have been valued and supported with enough data to be included in databases such as the Ecosystem Service Valuation Database, from where the monetary estimates were obtained. This means there is an underrepresentation of ecosystem services. As a result, thereof, the priority of including aesthetic value might actually be higher than proposed by our analysis.

The second aspect to consider includes the decisions made during the prioritization to match the ES types from de Groot et al. (2012) with our proposed ES categories (See description in Supporting information). For example, the category “Raw materials” used by de Groot et al. (2012), which is based on the TEEB classification, contains estimates of biomass materials as well as minerals and ore-based materials. However, the specific values for each type were not available, and therefore we attributed all monetary values of the “raw materials” category to our “Biomass provision” category, which results in a slight overestimation of this category within our ranking. Another consideration regards the ecosystem services categories of “water conditions” and “mediation of wastes, toxics and nuisances”. They are ranked at the same level since they are presented together in the category “waste treatment and water purification” by the TEEB (Van der Ploeg et al., 2010). Finally, the prioritization was done entirely based on the monetary valuation, whereas ideally a ranking of ES according to those most impacted by the technosphere could also have been considered. Unfortunately, the lack of comprehensive data on impacted ES hampered including this in the analysis. Despite the limitations of ecosystem services economic valuation, it also has several advantages. For example, monetary valuation data of ES is available and easily accessible (for example the Ecosystem Services Valuation database by Van der Ploeg et al. (2010)), and the use of monetary units can facilitate the communication of economic benefits that, for example, would be lost if ES were destroyed.

2.4.3 Aggregation of the optimal coverage

Given that our analysis shows that the majority of ecosystem services categories (11 out of 15) that may be impacted by the technosphere are not yet considered in LCAs, creating the proposed optimal state will imply a need to develop a large number of midpoint indicators. Our prioritization analysis can serve as a guide for future research by indicating the ES categories that present the “highest priority” based on available monetary data. In addition, a high number of indicators may be considered difficult to handle in decision-making processes (Cucurachi et al. 2016). The weighting step in LCA has the explicit intention to address this problem by further aggregating the indicator results using normative weights and thus facilitate decision-making (Cucurachi et al. 2017). While this weighting process is sometimes debated within LCAs, for ES this method is well-developed ensuring that all ecosystem services are expressed in the same units through e.g., monetary valuation. Given that comprehensive databases are available for monetary valuation (such as de Groot et al. 2012), this process may be facilitated by a cross-fertilization between the fields of LCA and ES.

Before weighting can be performed, the various indicator results will first need to be transposed into the same units, for which normalization is one possibility (Guinée et al. 2002). Therefore, normalization factors may have to be developed for new ES impact categories. For instance, if a new impact category such as “Biomass consumption” or “Decrease on biomass production” is included in LCA, a normalization factor needs to be provided, such as “total biomass produced” in the world at a certain year. Some inherent problems of normalization will have to be taken into consideration such as normalization bias, compensation, magnitude insensitivity, etc. (Cucurachi et al. 2017; Heijungs et al. 2007; Prado et al. 2017). Another option is to aggregate or model midpoint indicator results into endpoint indicator results. However, also this requires weighting. As an example of this, Cao et al. (2015) proposed the aggregation of six midpoint land use indicators into an endpoint representing the loss of ecosystem services captured by human society. Ultimately, this could lead to an endpoint on ''ecosystem service impact'' which captures all impacts of the technosphere on ecosystem services.

2.4.4 Implementation of future indicators

Ecosystem services depend on natural properties and functions that differ across the globe due to biogeographical variations, making spatial differentiation a crucial aspect for their assessment. If impacts to ES are to be included in LCA, it is essential that their estimation is done by taking into account biogeographical variations (Koellner et al. 2013; Maes et al. 2012). As described previously, several indicators have been proposed in the literature for the assessment of ES in LCA (Beck et al. 2010; Brandao and I Canals 2013; Cao et al. 2015; Koellner et al. 2013; Langlois et al. 2015; Maes et al. 2016; Mila i Canals et al., 2007b; Núñez et al. 2013; Saad et al. 2013; Taelman et al. 2016; Vidal Legaz et al. 2017), through the incorporation of new impact categories in impact assessment methods and newly developed characterization factors.

Geographical specificity has been attempted for some of the indicators by developing characterization factors at a diverse range of spatial scales (Saad et al. 2013). However, their use is limited due to practical complications involving spatial compatibility with inventory flows of background processes, and has been restricted mainly to foreground processes in the case of LCA. As described by Heijungs (2012), most background processes lack the precise geographical information to connect the emissions with highly site-specific characterization factors. Furthermore, pursuing a hyper-regionalization of the impact assessment phase in LCA would lead to "a complete breakdown of the feasibility of matrix-based LCA" (Heijungs 2012).

To reach a compromise between the need for spatial differentiation for ES and the practical limitations of LCA, we propose further research to focus around the use of archetypes (see for example Gandhi et al., 2011b, 2011a; Kounina et al. 2014) to develop spatially differentiated characterization factors that can be linked with background processes. Most background processes are categorized at a maximum geographical resolution of country level. However, biographical variations can be reflected with the use of archetypes by assigning each country to an archetype category, and therefore reducing the number of spatial categories needed for the assessment of ES. Archetypes can take into account environmental and socioeconomic factors to have a more accurate representation of the studied system (Kounina et al. 2014; Václavík et al. 2013). The use of archetypes would allow estimating impacts on ES also for background processes, increasing the applicability of newly proposed indicators.

2.5 Conclusion

Our study proposes an optimal state for the coverage of ecosystem services in LCA composed by fifteen ES categories derived from CICES V5.1 (2018). The categories that are still missing from the assessment of LCA, and specifically from ReCiPe2016, should be integrated in the most explicit way possible to prevent and avoid double counting of overlapping categories. Our prioritization of ES categories missing can be used (and improved) as an indication of which ES require more attention and rapid integration in impact assessment methods to avoid their continuing degradation and loss of benefits to human well-being. The list of ES categories provided in this study helps shedding a light on the increasing number of impact categories needed for incorporation in LCA. The incorporation of impact categories and characterization factors will require interdisciplinary cooperation to develop models that can be used in LCA and that can remain representative of the (spatial differentiation in) natural processes and effects that are desired to assess.

2.6 Supporting information

All supporting material is available online via:

https://ars.els-cdn.com/content/image/1-s2.0-S0959652619318207-mmc1.docx

https://ars.els-cdn.com/content/image/1-s2.0-S0959652619318207-mmc2.xlsx

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Chapter 3

Characterization model approach for LCA to estimate land use impacts on pollinator abundance and illustrative characterization factors

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Abstract

This study presents the first approach to characterize relative land use impacts on pollinator abundance for life cycle assessment (LCA). Pollinators make an essential contribution to global crop production and in recent years evidence of declines has raised concerns on how land use, among other factors, affects pollinators. Our novel method assesses land use impacts on pollinator abundance and proposes a new impact category that is compatible with the current framework of life cycle impact assessment (LCIA). While a systematic literature research showed the existence of multiple models that could assess pollinator abundance impacts, their parameterization is too complicated for applications in LCA. Therefore, a simplified method based on expert knowledge is presented. The practical application of the method is illustrated through the connection to, and characterization of, relevant land use types derived from the widely used LCA database, ecoinvent. The illustrative characterization factors demonstrate that key differences among land use types can be reflected through the proposed approach. Further development of robust characterization factors through a larger sample of pollinator abundance estimates, and improvements to the model, such as considerations of spatial differentiation, will contribute to the identification of impacts of agricultural practices in LCA studies, helping prevent further pollinator abundance decline.

Keywords: Ecosystem services; Pollination; Life cycle assessment; Pollinator abundance

3.1 Introduction

In recent years, pollinators have attracted wide attention due to their alarming decline rates and their essential role in global food security (IPBES 2016). Around three quarters of the leading food crops around the world depend, at least in part, on insect pollination (Klein et al. 2007; Stein et al. 2017). Pollinators include many groups of insects, though bees are recognized as the most important taxa of crop pollinators across the globe (Klein et al. 2007; Potts et al. 2016) and their service has a positive influence not only on crop yield but also on the quality of pollinator-dependent crops, increasing fruit and seed production (Garratt et al. 2018; Motzke et al. 2015; Stein et al. 2017). Pollinator declines are due to a variety of factors, with the main drivers considered to be land use change (Carvalheiro et al. 2010; Koh et al. 2016), agricultural intensification, including the use of agrochemicals such as pesticides (Kennedy et al. 2007; Samson-Robert et al. 2017; Stanley and Raine 2017), climate change (Hannah et al. 2017; Radenković et al., 2017), pathogens and alien invasive species (Crenna et al. 2017; Potts et al. 2016). Understanding the effect and intensity of impact drivers is essential to prevent further decline of pollinators and their associated negative consequences.

Global food security, already affected by impact drivers such as climate change, waste, increasing demand and soil degradation (Dhankher and Foyer 2018; McCarty 2018) might be further jeopardized by the severe declines observed of wild pollinators in parts of Europe and North America, and which could potentially be happening in other parts of the world as well (Hallmann et al. 2017; Novais et al. 2016; Vasiliev and Greenwood 2020). To help prevent further decline, impact assessments can be a useful tool to show environmental impacts associated with a variety of production systems and industries (Alejandre et al. 2019; Crenna et al. 2019). Nowadays the most commonly applied method is Life Cycle Assessment (LCA). This method has been standardized by the International Organization for Standardization (ISO 14040–14044) and it allows to quantify the potential environmental impacts associated with a product system over its entire life cycle (Guinée et al. 2002; Hellweg and Canals 2014; ISO 2006). Product systems are defined in LCA as the set of unit processes interlinked by material, energy, product, waste or service flows, performing one or more defined functions (Guinée et al. 2002). During the impact assessment phase, environmental interventions are translated into potential impacts with the use of characterization factors that are provided by impact assessment methods. However, current impact assessment methods used for LCA, such as ReCiPe2016 (Goedkoop et al. 2013; Huijbregts et al. 2016), LC-Impact (Verones et al. 2016) and Impact World+ (Bulle et al. 2019) do not account for impacts on pollinators or pollination. Given the essential role of pollination in global food security and the ability and wide use of LCA to evaluate a wide range of environmental interventions and potential impacts, it is crucial to address this omission by proposing a new impact category that focuses on pollinators, and to develop an impact assessment model to produce the aforementioned characterization factors for use in LCA.

To produce new impact categories for LCA, one of the biggest challenges is to connect highly specific and complex impact models to LCA inventories which are often coarse and oversimplified (Schmidt 2008). This paper tackles this specific challenge and addresses the development of a new impact model on pollinators. This new model includes pollinators as an impact category and provides the related characterization model in LCA. Based on the review of Crenna et al. (2017) on potential impact drivers on insect pollinators, this study focusses on pollinator impacts driven by land occupation. To exemplify the operationalization of the characterization model proposed, this study presents more than 50 illustrative characterization factors for a range of land use types that are compatible with one of the most extensively used databases for LCA, ecoinvent (Wernet et al. 2016).

To achieve this aim, the general requirements for new impact categories in LCA are discussed first and it is analysed if and how pollination impact pathways fit within the general structure of LCIA (Life Cycle Impact Assessment). Next, the selection of a suitable pollinator impact models is discussed. This selection explicitly accounts for complications that may arise from the geospatial incompatibilities between the pollinator impact model and the geographical scales available in LCA inventories (Mutel et al. 2019; de Baan et al. 2013). The most feasible way to develop applicable characterization factors for land use impacts on pollinators, accounted for this spatial mismatch is presented. The applicability of the approach is illustrated by showing globally applicable characterization factors based on relative estimates of pollinator abundance for a variety of land types as provided by expert knowledge. Finally, possible improvements regarding this topic as provided in the discussion section.

3.2 Methods

The steps taken in this study to develop a novel method for assessing land use impacts on pollinator abundance, are summarized in three main sections below (See Fig. 3.1): the selection of an impact category taking into consideration the limitations and current structure of LCA is followed by the selection and derivation of a characterization impact model, and finally by the calculation of characterization factors that can be used in LCA.

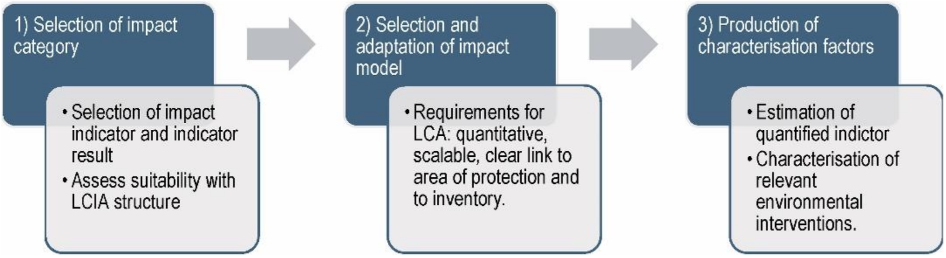

Figure 3.1 *Methodological steps and considerations.*

3.2.1 Selection of a midpoint impact category

3.2.1.1 Key characteristics and considerations for LCA

Any proposal for a new impact category for LCA should follow the general structure of the life cycle impact assessment (LCIA) phase and ensure the new category is compatible with existing impact assessment methods to guarantee applicability (a detailed description of LCIA can be found in the Supporting information). To achieve this compliance, the most appropriate indicator for a midpoint impact category was determined. When it comes to pollination, this service is a function of supply and demand that varies depending on the location, type of crop, type of pollinators and season, among other aspects (IPBES 2016).

Currently most of this data is completely absent from the LCA inventory, making the high spatial variability of pollination services one of the main constraints for their estimation in LCAs. However, instead of assessing the service of pollination as midpoint, the pollinator abundance can be used. The capacity to provide pollination services has been shown to be strongly correlated with pollinator abundance (Koh et al. 2016; Lonsdorf et al. 2009). Assessing impacts on pollinator abundance is thus an appropriate alternative. This alternative is feasible and compatible with the current LCIA structure since pollinator abundance can be directly estimated based on the land use/cover types for which information is available in LCA. Moreover, pollinator abundance as a midpoint category resembles an environmental property and as such complies to general definitions of midpoint impact categories (Othoniel et al. 2016; Rugani et al. 2019). Thus, the scope of our study is to present an impact model that can estimate pollinator abundance impacts associated with land use/cover types, specifically focusing on wild pollinators (See Fig. 3.2).

Land use impacts are usually characterized in LCA for two types of interventions: occupation and transformation (Koellner et al. 2013). Occupation impacts refer to the change in quality of a given land during its time of use, while transformation impacts refer to the change in quality due to land use or cover change. The impact of these land use interventions is calculated amongst others by estimating the change of an ecosystem quality (ΔQ) over a certain period of time, with the characterization factor (CF) for occupation impacts calculated as the change in the quality ($CF_O = \Delta Q$), and for transformation impacts as the change in quality multiplied by a regeneration time (t_{reg}) and assuming a linear recovery between the two states ($CF_T = \Delta Q \times t_{reg} \times 0.5$). If the same ΔQ value is used for the calculation of both occupation and transformation impacts, there is a risk of incurring on double counting. Currently, most agricultural background processes in ecoinvent present a link to both occupation and transformation flows of the same size, with most processes presenting the same land use type in the transformation from-and-to flows (See examples in Supporting information). Taking into consideration the risk of double counting, this study focuses on land use occupation impacts to illustrate the characterization model proposed and the derivation of CFs.

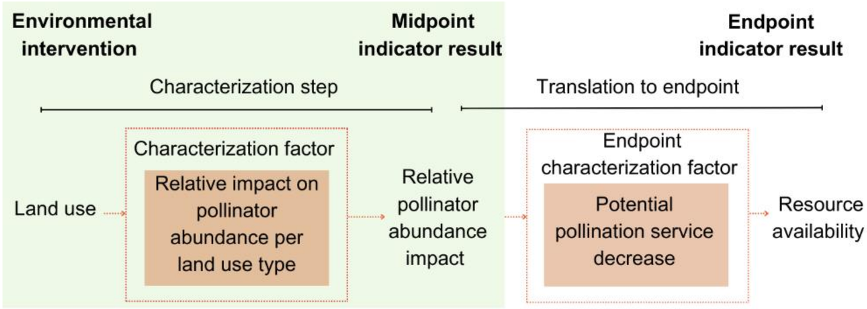

Figure 3.2 *Conceptual diagram of the structure for a new impact category assessing land use impacts on pollinator abundance. The scope of this study is delimited within the green box.*

3.2.1.2 Connection to background inventory

It is important that new impact categories, related models and characterization factors, are compatible with 'background processes'. Background processes define the relationship between unit processes, which are the smallest portion of a product system for which data are collected in a LCA (Guinée et al. 2002) and products based on databases, without needing input from a LCA practitioner. One of the most widely used databases around the world for LCA is the ecoinvent database (https://www.ecoinvent.org/), which contains several thousands of interlinked background processes that can have a substantial weight in the LCA results (Heijungs 2012). Therefore, compatibility with the inventory of background processes is an important consideration when developing characterization models, to avoid the resulting characterization factors to be limited to foreground processes (i.e., processes defined by the LCA practitioner).

To illustrate the operationalization of the proposed model with existent background processes, we analysed relevant land use processes and inventory data from ecoinvent. For this, the ecoinvent database version 3.4 'cut off' (https://www.ecoinvent.org/) was assessed with OpenLCA version 1.8.0 for Windows (http://www.openlca.org/). Every process in the database includes 'elementary flows' reflecting an emission, a use of a resource or land use, either entering (resource and land use) or leaving (emissions) the product system under study (Guinée et al., 2002). These elementary flows allow tracing and accounting of the total emissions and resources related to a product system, and are translated by characterization factors into potential environmental impacts. We created an inventory of the relevant land use types found in elementary flows (Table 3.1). We only included elementary flows that were already linked to background processes and relate to agriculture and/or natural land (full list in Supporting information). We did not include flows relating to the occupation of industrial sites, construction areas, or mineral extraction sites, since the pollinators abundance of those land use types can be assumed to be null.

Table 3.1 *Summary of the land use types derived from elementary flows connected to agricultural processes in ecoinvent.*

Elementary flows - Land occupation	
1	Annual crop
2	Natural grassland
3	Man-made pasture
4	Permanent crop
5	Shrub land
6	Cropland fallow
7	Forest

3.2.2 Impact models in the literature targeting pollinator abundance

To retrieve impact models from the literature that can be used to estimate pollinator abundance based on land use types, we conducted a bibliometric analysis in the ISI Web of Science (WoS) published by Thomson Reuters, using as keywords 'pollinator abundance' AND 'impact model' (accessed on 19/11/2018). This provided models from both the ecological and the LCA scientific community. To be selected, models had to comply with the specific criteria in order to be considered for a new LCA impact category (see Box 1).

Models that did not fulfil all of these basic requirements were not considered for LCIA within the scope of this research.

Box 1. Criteria used to select impact models for a new impact category in LCA:

1) The model should allow for quantitative estimations: LCIA is a phase of LCA where potential contributions of environmental interventions from LCI (e.g., emissions, resources use, land use) to impact categories (e.g., climate change, acidification, resource depletion, pollination) are quantified by multiplying these interventions with characterization factors derived from scientific impact models and aggregating the results into indicator results for each impact category.

2) The model can be linked with inventory data: During the inventory phase the product system is defined and the data for each unit process is collected. However, a crucial limitation of LCA is the availability of data. The impact model proposed should be able to use data that are currently present in LCA inventories or that can be added in a way compatible with LCA inventories (UNEP/SETAC 2016).

3) A clear link to an area of protection: The three areas of protection (AoP) currently assessed in LCA are Ecosystem quality, Human health and Resource availability. Within each, there are multiple endpoint categories that could be developed and represent impacts in one or multiple AoP (UNEP/SETAC 2016).

4) Scalable with a functional unit: A functional unit is the quantified function provided by the product system(s) under study, for use as a reference basis in an LCA (Guinée et al. 2002). All impact results are scaled in a linear way in accordance to the functional unit defined for each study (Heijungs 2020).

3.2.3 Characterizing pollinator abundance

Once a suitable impact model was found and derived from the literature, we proceeded to analyse how it could be used as a characterization model within the LCIA framework while complying with the LCA requirements (described in the previous sections). Characterization models link and quantify the potential contribution of elementary flows to a specific impact with the use of characterization factors (CFs; see section 3.2.1.1). The elementary flows of ecoinvent represent coarse land use types such as for example ‘permanent crop’, ‘forest’, etc. However, independent of elementary flows, ecoinvent contains more detailed information at a processes level, such as type of crops. To utilize this additional information, we characterized both the list of coarse land use types from elementary flows, and the additional categories derived from the agricultural processes available for non-perennial and perennial crops (Fig. 3.3). For non-perennial crops, the database contains 45 type of crop processes, ranging from cereals to fibre crops, and there are 29 perennial crops available, ranging from fruits to spices. Additionally, considering the current limitations for biogeographical differentiation in LCA, we will focus on presenting a global characterization model and derive the preliminary characterization factors world generic estimates.

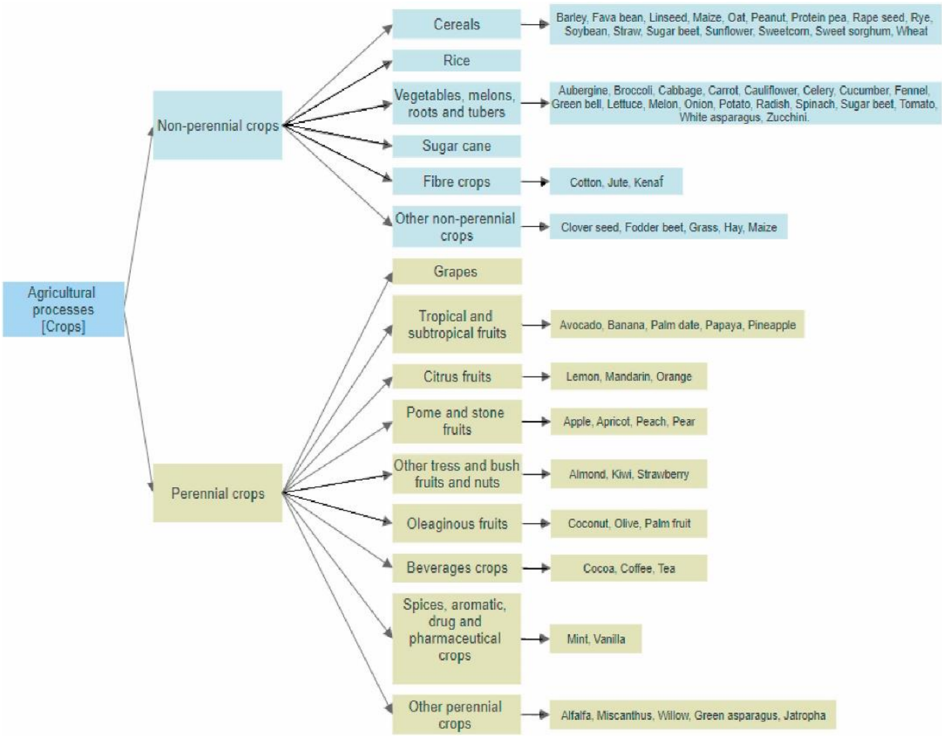

Fig. 3.3 *Inventory of agricultural crop processes found in ecoinvent (https://www.ecoinvent.org/).*

3.3 Results

3.3.1 Impact model selected from the literature

The bibliographical search resulted in 65 studies. From these, studies targeting climate change or toxicity by pesticides in their impact model were out of the scope of this study. We found that the majority of studies assessing pollinator abundance based on land systems have applied the Lonsdorf model (Lonsdorf et al. 2009) or an adaptation of it. The Lonsdorf model is a spatially explicit model that predicts relative bee abundance based on the composition of habitats and their floral and nesting resources, and it relies on simple land cover data and established pollinator behaviour as governed by a few key parameters. Based on the criteria described in section 3.2.2 we found that the Lonsdorf model complies with the general requirements for LCA: 1) The model allows a quantitative estimate of pollinator abundance with a linear model; 2) The relation between land use (type and amount) and pollinator abundance can be directly linked with inventory data which provides information on the land use type and amount of land used; 3) The link between pollinator abundance and at least one of the areas of protection covered with LCA can be modelled through either 'Resource availability' and/or 'Ecosystem quality'; and 4) the environmental intervention assessed with this model and its estimated impact is scalable to a functional unit. Given compliance to these main four criteria, we concluded that the model could theoretically be used to calculate characterization factors for a midpoint impact category for LCA.

3.3.1.1 The Lonsdorf model

The first part of the Lonsdorf model consists of using the landscape structure and vegetation community of a given area to determine the possible community of pollinators available and their abundance. The result of this first part is a spatially explicit estimate of the relative abundance for each species or guild across a given landscape. This first part of the model can be applied to estimate the pollinator abundance of, for example, land use/cover type 'x'. The resulting estimate can be used as the characterization factor for land use type x, which would represent the pollinator abundance associated to land use type x. Alternatively, if there is enough information of a certain land use type at two different states (e.g., before and during land use x), the first part of the Lonsdorf model can be used to estimate the pollinator abundance at the two states of land to derive the change in quality (ΔQ) due to a specific land use or management. The result would correspond to the characterization factor.

Using the Lonsdorf model to determine the potential change in pollinator abundance associated with land use can provide robust results in terms of spatial and temporal representativeness. However, exact application of the model would require a large standardization and quantification of data to produce harmonized and comparable results. Given the high number of location-specific parameters in the model, representative CFs should be the product of a meta-analysis that can adhere to the model assumptions, use standardised data (e.g., standard land cover maps), and preferably validated with field observations. Additionally, it would be necessary that a panel of experts evaluates the nesting suitability for each of the bee nesting guilds (e.g., ground, cavity, stem, and wood-nesting bees) and floral resource availability for the foraging seasons considered (e.g., spring, summer, fall), for each land use type studied. Such evaluation was beyond the scope of this study and therefore we derived a simplified method.

3.3.2 Alternative approach

3.3.2.1 The simplified method

Considering the demands for application of a pollinator impact model within an LCA context, we derived an alternative approach that minimizes the number of parameters to be characterized by "bypassing" the Lonsdorf model and utilizing expert input to obtain relative pollinator abundance values. This approach also allows the CFs to be linked with background processes by specifically characterizing the land use types derived from the ecoinvent database. We refer to this approach as the simplified method. Similar to the Lonsdorf model, it relies on expert knowledge to determine pollinator abundance for each land cover data. To do this, our method requires experts to assign a score of pollinator abundance to each land use/cover type. Since LCA results are relative values and not absolute, we can use an averaged pollinator abundance per land use/cover type to derive the CFs and portray the differences among product systems by accounting for the types of land use/cover involved on each system.

To illustrate the simplified method, the inventory of relevant elementary flows and of agricultural crop processes was characterized by a pollinators' expert who attributed a mean estimate of the pollinator abundance (denominated here as S_x) that can be expected or associated with each land use type (this 'mean' estimate refers to the most predominant values and not specifically to the statistical mean, therefore it refers to the 'mode' of pollinator abundance values). Assigning each land use type with a quantitative score, serves as a proxy to represent its capacity to provide an ecosystem service or function. In this case, the quantitative score was given to each land type to reflect their relative pollinator abundance. The estimates varied from 0 to 100, starting by assigning the highest value to a reference state of optimal pollinator abundance. Open phrygana (also called garrigue) in Mediterranean ecosystems had a value of 100 and thus coincided in terms of pollinator abundance with the reference state, but is not to be confused with a potential natural vegetation. Values between 50 and 100 were attributed to land use types that have a high relative pollinator abundance, while values between 0 and 50 correspond to land use types that are likely to present low to none pollinator abundance. The estimates thus describe the relative impact on pollination associated with each land use type. Additionally, a score for low and high rates of pollinator abundance was given for each land use type (the full table of pollinator abundance estimates for each land use type can be found in the Supporting information) to account for impacts of differences in management within a land use type.

While several reference states can be used for the characterization of impacts, such as potential natural vegetation (PNV), the prior land use state, or a mix (Koellner et al. 2013), the CFs produced through this approach express relative pollinator abundance decrease in reference to an optimal state, which in this study corresponds to a land use type of open phrygana. Given that the CFs produced in this study are for occupation impacts and world generic, the reference state is only used during the characterization of the relative impact that is attributed to each land use type, and unlike the PNV, it does not imply that the land would naturally regenerate to the optimal state.

3.3.3 Application for LCA

3.3.3.1 The quantified indicator

The quantified indicator for this newly proposed impact category is then pollinator abundance (PA) in reference to the land use type with the maximum value (100) of pollinator abundance (PA_{ref}), which in this case coincides with open phrygana. The value of 100 represents an undetermined number of pollinators per m^2 of reference land use type, written as α:

$$PA_{ref} = \alpha$$

The number α is expressed in pollinator individuals per m^2. This number is difficult to specify exactly, but there is no need to do that as we define pollinator abundance only relatively. For any other land use type, say x, we express the pollinator abundance as (PA_x, in pollinators/m^2):

$$PA_x = \frac{S_x}{100}\alpha$$

with S_x as an expert estimate of the pollinator density on a scale from 0 to 100, relative to the reference state, which in this study corresponds to open phrygana. This quantified indicator is used to derive characterization factors.

3.3.3.2. Deriving characterization factors

To derive the characterization factors for impacts of land occupation on pollinator abundance, we analysed the change in number of pollinators per unit area of land use type x, compared to the reference state:

$$CF_{O,x} = \Delta PA_x = \propto - \frac{S_x}{100} \cdot \alpha = \left(1 - \frac{S_x}{100}\right) \cdot \alpha$$

Because the number α is unknown, we prefer to work with CFs relative to a reference condition of optimal pollinator abundance. This then yields:

$$CF_{O,x} = 1 - \frac{PA_x}{PA_{ref}} = 1 - \left(\frac{\left({S_x}/{100}\right) \cdot \alpha}{\alpha}\right) = 1 - \frac{S_x}{100}$$

The CF for open phrygana is 0, while for complete pollinator-free land use types, it is 1, and for land use x with S_x = 40 the CF will be 0.6 indicating 60% lower pollinator abundance compared to the reference state. These CFs are dimensionless in the same way as the IPCC (2013) global warming potentials (GWPs) are dimensionless: The GWPs express the time-integrated increased infrared absorption due to an emission of 1 kg of a given greenhouse gas (GHG) relative to an equal emission of carbon dioxide, which results in dimensionless characterization factors (kg GHG/kg CO_2). The GWPs are then multiplied with inventory emissions of GHGs (kg GHG) and aggregated to an indicator result for climate change expressed in kg of CO_2 equivalents. In the same way, our CFs are 'dimensionless' (m^2·year/m^2·year reference land) and relative, expressing the time-integrated decrease of areal pollinator abundance (expressed in terms of number of pollinators per m^2) of, for example, land occupation $\boldsymbol{x}$, relative to the time-integrated areal pollinator abundance of the reference land:

$$\frac{\left.\frac{pollinators}{m^2}_{x}\middle/ m^2 \cdot \text{year}_{O,x}\right.}{\left.\frac{pollinators}{m^2}_{ref}\middle/ m^2 \cdot \text{year}_{O,ref}\right.} = \frac{m^2 \cdot \text{year}_{O,ref}}{m^2 \cdot \text{year}_{O,x}}$$

The CFs (m^2·year/m^2·year reference land) are multiplied with their corresponding land occupation interventions (in m^2·year), that results in an indicator result in m^2·year reference land (further described in Section 3.3.3.4).

3.3.3.3. Illustrative characterization factors for impacts on pollinator abundance

To illustrate the simplified method, we present the characterization procedure and illustrative CFs that are obtained for the land use types evaluated in this study. The pollinator abundance estimates were provided by one pollinator expert based on existing literature and consistent with general trends prevailing in pollination assessments (e.g., IPBES 2016). These values should thus not be interpreted as a consensus of expert knowledge on the scores of each land use type.

The CFs for the aggregated land use types derived from elementary flows are presented in Table 3.2. These aggregated values allow directly connecting to current background processes and were estimated directly by expert assessment (i.e., considering all possible land use within each category). To additionally present the CFs of the 42 non-perennial and perennial crops, we derived and aggregated values of each crop within sub-categories as shown in Fig. 3.3, and present them in Tables 3.3 and 3.4, accordingly. These CFs express the potential contribution to the impact category of pollinator abundance, relative to a reference state. The result can thus not be used for absolute decisions (Guinée et al. 2017).

One should thus only use the CFs for comparing alternative products. Furthermore, it is important to consider the full suite of environmental implications when interpreting LCA results, to identify potential trade-offs.

3.3.3.4. Implementation in LCA: the indicator result

For calculating the indicator result for all land occupation flows related to a specific LCA case study, all occupation flows (O_x) are multiplied by their respective characterization factors $CF_{O,x}$ and their results are aggregated into the indicator result PAO:

$$Pollinator\ Abundance\ Occupation\ (PAO) = \sum_{x=1}^{x=n} \left(CF_{O,x} \times O_x\right)$$

where O_x is the time integrated area of occupation in $m^2\cdot$ year. The unit of the indicator result PAO is thus also $m^2\cdot$year. The indicator result allows to compare the relative pollinator abundance decrease that is associated with each product system, as a result of the land use types involved in each. For example, systems relying mainly in non-perennial crops will present a higher pollinator decrease compared with systems relying mainly on permanent crops.

Table 3.2 *Illustrative characterization factors for aggregated land use types derived from elementary flows from ecoinvent.*

Aggregated land categories	Pollinator abundance (PA)	Characterization factor ($\mathbf{CF = 1 - \frac{S_x}{100}}$)
Annual crops	20	0.80
Natural grasslands	70	0.30
Man-made pastures	35	0.65
Permanent crops	40	0.60
Scrubland	60	0.40
Cropland fallow	50	0.50
Forest	40	0.60

Table 3.3 *Illustrative characterization factors for non-perennial crops derived from agricultural processes present in ecoinvent.*

Categories of non-perennial crops	Pollinator abundance (PA)	Characterization factor ($\mathbf{CF = 1 - \frac{S_x}{100}}$)
Cereals	17	0.82
Rice	10	0.90
Vegetables, melons, roots and tubers	25	0.75
Sugar cane	10	0.90
Fibre crops	40	0.60
Other non-perennial crops	16	0.84

Table 3.4 Illustrative characterization factors for perennial crops derived from agricultural processes present in ecoinvent

Categories of perennial crops	Pollinator abundance (PA)	Characterization factor ($\mathbf{CF = 1 - \frac{S_x}{100}}$)
Grapes	25	0.75
Tropical and subtropical fruits	25	0.75
Citrus fruits	35	0.65
Pome and stone fruits	35	0.65
Other trees and bush fruits and nuts	28	0.72
Oleaginous fruits	25	0.75
Beverage crops	25	0.75
Spices, aromatic, drug and pharmaceutical crops	35	0.65
Other perennial crops	32	0.68

3.4 Discussion

3.4.1 Scientific and methodological advances

This study proposes a modelling approach that is compatible and applicable with current LCA methods and inventories, and form the basis for future improvements for the assessment of impacts on pollination. One of the first innovations was to define pollinator abundance as the target for a midpoint category, instead of targeting pollination service at endpoint as it had been proposed in the literature (Crenna et al. 2017). While pollination service delivery is highly correlated with the abundance of the most common pollinators, it is also correlated with pollinator diversity (IPBES 2016). We made a pragmatic decision to address only pollinators abundance at midpoint since models such as Lonsdorf et al. (2009) correlate landscape characteristics with pollinators abundance. Species richness may be included in the translation from abundance into service delivery, which we propose to be the target for the endpoint category. By targeting pollinator abundance, we were able to integrate a new impact category in LCA that is compatible with the current structure of LCIA and that can be linked with existing information from LCA inventories.

The connection to background processes is currently essential to aim for a wide applicability of the CFs produced. This study is one of the first to address this particular issue when proposing new land use related impact models for LCA. The lack of connection to background processes can render new models to fall behind as the potential impact results cannot reflect the influence of the grand majority of processes within the product system studied. For our study, we specifically characterized land use types retrieved from the widely used LCA database ecoinvent. While these land use types are coarse and lack important biogeographical differentiations, they present an opportunity to utilize the existing data available in LCA inventories and allow characterizing the potential impact to pollinator abundance by using a simplified approach based on expert knowledge. Through expert knowledge, empirical knowledge regarding observed trends of pollinator abundances were integrated, consistent with results found in the literature that rely on both predicted and sampled data. The results indicate that the CFs reflect key differences among land use types. Further validation tests will be done in follow up research projects aimed at further improving the accuracy of the characterization factors with input from a broader range of experts.

3.4.2 Limitations and potential improvements

While the simplified approach allows us to characterize current inventory flows from ecoinvent related to agricultural lands, the approach does not allow to capture critical local sources of variation through its use of broad land use types and crop processes. It also does not take into account the full range of drivers of pollinator communities such as local management, the local species pool and impact sources such as mortality caused by pesticides or pathogens. As part of our bibliographical search for impact models targeting pollinators, we found that climate change impacts depend highly on indirect effects linked for example with temperature and precipitation changes, forest health, and soil attributes (Hannah et al. 2017; Radenković et al. 2017), and the pesticides impact models are highly specific to the case studies in which they are applied, which is an inherent characteristic of toxicity impacts on pollinators (Godfray et al. 2014). Therefore, these models were not considered to be yet readily compatible and applicable within an LCA context and therefore these impact drivers were not considered in our current proposed model. Furthermore, we found several studies assessing the influence of landscape on pollinator abundance (Brandt et al. 2017; Kennedy et al. 2007; Matteson et al. 2013; Ricketts and Lonsdorf 2013; Sérospataki et al. 2016). Other studies addressed specific aspects that can influence pollinator abundance such as pollinator body size (Benjamin et al. 2014), pollinator habitat and its effect on visitation probability (Schulp et al. 2014), and the influence of bee species traits (De Palma et al. 2015). However, the Lonsdorf was found to be the most widely used landscape-pollination model in the literature and its application for LCA is suitable, which is why we focused our study on this single model. Looking into specific characteristics of the models and the land use types assessed, both the Lonsdorf model and the simplified method assume that the population of pollinators is static. This can be seen as both a limitation and an advantage, since it cannot reflect the changes of population size across time, but it allows both methods to be applied within the LCA framework where temporal scales are currently not available in inventory data. Further improvements could target the inclusion of additional impact models regarding pesticide use and/or climate change impacts on pollinators. Such may be achieved by increasing the detail of inventory background processes to include, even if it is generalized, data on management practices regarding for example pesticide application rates, irrigation, seasonal rotations or connectivity in the landscape, would allow to derive CFs that can take these differences into consideration when providing the pollinator abundance estimates without having their application limited to foreground processes.

The characterization approach is illustrated in this study through the world generic CFs. To produce regionalized CFs for this new impact category, it would be necessary to select the appropriate geographical scale, the additional reference state per geographical unit (e.g., PNV), and matching of land use categories depending on the data sources used. It is recommended for future research to complement the development of regionalized characterization factors with a clear overview of the connection to background processes and the necessary adaptations (if any) of the LCA inventories for the application of regionalized CFs.

Additionally, while wild pollinator abundance is driven (at least in part) by land use, the abundance of managed honeybees, the most important global pollinator species, is primarily driven by beekeeper and farmer decision making (which may be indirectly linked to land use, but not always). Therefore, it is important to recognise that our proposed method only addresses wild pollinators and not managed pollinators. This is an important first step towards a comprehensive model, given that wild pollinators are widely documented as being at least as important, and often more important than managed honeybees for crop pollination (IPBES 2016). Further improvements can be aimed at incorporating new inventory processes in ecoinvent that can include managed pollinators and remediation practices, for which the characterization factors would be negative values indicating positive impacts. That way, comparisons in LCA of agricultural practices could explore possibilities for prevention and remediation in the design of their product systems or in sensitivity analyses, allowing LCA practitioners to recommend changes or better strategies to reduce impacts on pollinators.

3.4.3 Outlook

Identifying the potential effects of land use on pollinators is an indispensable aspect to consider during decision making, and impact assessments can be instrumental to raise awareness and help prevent further decline rates. We have been able to further expand the reach of LCIA, by allowing LCA practitioners to consider pollinator impacts when assessing the potential environmental interventions of a product system. Through the development and integration of this new impact category and its corresponding impact model to produce robust CFs, we provide LCA practitioners with a prior account of impacts while comparing among product systems. This will be beneficial, for example, when comparing between crops for biofuels purposes, for food production systems, or when assessing different scenarios for land management. This will facilitate the identification of product systems with high impacts on pollinator abundance and allow practitioners to recommend preventive or remediation actions. In addition to allowing a comparison of product systems, based on their potential environmental impacts including those on pollinators, it also allows the identification of impact hot spots within product systems. In addition to preventing environmental impacts, such actions will likely also provide economic benefits given the critical role of pollination in securing crop productivity. Therefore, securing pollination will increase the competitiveness of agriculture and its resilience to future change.

Before such large-scale application, the model proposed in this study needs further evaluation. Our method was operationalized by producing illustrative CFs that reflect key differences among crops and land use types. However, it is important to bear in mind that these values were obtained from the expert knowledge of one pollinator expert who provided the scores for each of the land use/cover types assessed in this study. Further improvements will target the collection of data from multiple experts to increase robustness and assess the associated uncertainty of the characterization factors. The same approach for the derivation of relative quantitative values proposed in this study can be also adapted to other impact categories for which absolute values are too complex to calculate at a worldwide level for an LCA application. This will allow incorporating knowledge from diverse fields, e.g., by multidisciplinary research groups. This will help to further improve the robustness of life cycle impact assessments and make it more comprehensive by adding highly relevant environmental impacts such as pollination.

3.5 Conclusions

This research highlights the need for incorporating pollination impacts within the assessment of LCA, due to their relevance in our current global food security and the urgent need to prevent further decline. We present a novel way to overcome current limitations in the structure of LCIA and the available LCA inventories by proposing an approach to account for pollinator impacts. We provide the required steps for the characterization of impacts, and illustrate the operationalization by producing preliminary characterization factors that are compatible with the ecoinvent LCA database. These characterization factors reflect key differences on the pollinator abundance associated with each land use type, including for the coarse land use types derived from elementary flows. Therefore, the application of the proposed approach and derivation of characterization factors from a larger sample of experts will result in applicable characterization factors compatible with background processes. Our novel approach could be further extended to incorporate other crucial components of biodiversity underpinning food and nutritional security, such as the effect of managed pollinators and potential spatial differentiations. The results of this study contribute towards the continuous improvement of the impact assessment methods for LCA, providing tools to assess key environmental impacts as comprehensively as possible.

3.6 Supporting information

All supporting material is available online via:

https://ars.els-cdn.com/content/image/1-s2.0-S0959652622006771-mmc1.docx

https://ars.els-cdn.com/content/image/1-s2.0-S0959652622006771-mmc2.xlsx

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Chapter 4

Characterization Factors to Assess Land Use Impacts on Pollinator Abundance in Life Cycle Assessment

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Abstract

While wild pollinators play a key role in global food production, their assessment is currently missing from the most commonly used environmental impact assessment method, Life Cycle Assessment (LCA). This is mainly due to constraints in data availability and compatibility with LCA inventories. To target this gap, relative pollinator abundance estimates were obtained with the use of a Delphi assessment, during which 25 experts, covering 16 nationalities and 45 countries of expertise, provided scores for low, typical and high expected abundance associated with 24 land use categories. Based on these estimates, this study presents a set of globally generic characterization factors (CFs) that allows translating land use into relative impacts to wild pollinator abundance. The associated uncertainty of the CFs is presented along with an illustrative case to demonstrate applicability in LCA studies. The CFs based on estimates that reached consensus during the Delphi assessment are recommended as readily applicable, and allow key differences among land use types to be distinguished. The resulting CFs are proposed as the first step for incorporating pollinator impacts in LCA studies, exemplifying the use of expert elicitation methods as a useful tool to fill data gaps that constrain the characterization of key environmental impacts.

Keywords: Pollinator abundance; Ecosystem service; Delphi expert elicitation; Agriculture; Impact assessment

4.1 Introduction

Pollinator communities around the world play a key role in agricultural production by influencing crop quality and yield (Bartomeus et al. 2014; Klein et al. 2007; Motzke et al. 2015; Ricketts et al. 2008; Stein et al. 2017). Wild pollinators, which provide long-term and effective crop pollination services (Graham and Nassauer 2017; Klein et al. 2007; Pfiffner et al. 2018), have been observed to decline in range and abundance in recent decades (Bennett et al. 2014; Koh et al. 2016a; Potts et al. 2010). While multiple factors, such as climate change and pesticide use, have been identified as drivers affecting pollinator communities (Fournier et al. 2014; Hannah et al. 2017; Imbach et al. 2017; Kennedy et al. 2013; Sabatier et al. 2013), land use and land management change remain a primary driver for the decrease in abundance (Barons et al. 2018; Brandt, Glemnitz, and Schröder 2017; Dicks et al. 2021; Le Féon et al. 2010; Macdonald, Kelly, and Tylianakis 2018).

This decline leads to potential mismatches between the provision of pollination services and the global demand for crop pollination (Garibaldi et al. 2008; Hallmann et al. 2017; Koh et al. 2016b; Lautenbach et al. 2012). Addressing the potential impact of land use on wild pollinators is therefore essential to help prevent further decline and identify better practices, and should be incorporated into commonly applied environmental assessment methods used worldwide such as Life Cycle Assessment (LCA) (Alejandre, van Bodegom, and Guinée 2019; Rugani et al. 2019).

LCA is an internationally standardized (ISO) method used globally to help estimate environmental impacts associated with a product system or service (ISO 2006). The estimation of impacts in LCA studies relies on the translation of inventory flows (which compile information such as resources and emissions) into impacts through the use of characterization factors (CF; numerical values representing the potential contribution to an environmental impact). Despite the relevance of wild pollinators, their assessment has not been explicitly incorporated in common LCA studies.

While recent efforts have provided recommendations for their incorporation in LCA (Crenna et al. 2017; Othoniel et al. 2016) and a characterization model (Alejandre et al. 2022), LCA studies currently still lack the ability to reflect impacts on pollinator communities since there are no readily applicable CFs that can translate environmental interventions into this specific impact. To address this gap, this study makes use of an expert elicitation assessment, the Delphi method, to obtain estimates of the relative abundance of wild pollinators associated with a variety of land use categories for the production of readily applicable CFs to assess land use impacts.

To guarantee compatibility of the resulting CFs with common LCA inventory flows, this study focuses on the characterization of land use categories found in the widely applied database ecoinvent (Wernet et al. 2016). Ecoinvent is one of the largest and most commonly used LCA databases around the world. The database contains information regarding unit process inputs and outputs, and provides in some cases country-specific information as well as global average values.

For this study, the relevant land use categories listed in ecoinvent are characterized to facilitate compatibility and direct application, and to encourage the incorporation of a category assessing impacts on pollinators in impact assessment methods, such as ReCiPe2016 (Huijbregts et al. 2017) and LC-Impact (Verones et al. 2016), among others (Bulle et al. 2019; Cao et al. 2015; Hischier et al. 2010). We expect the application of the resulting CFs to be a first step towards a more comprehensive assessment of land use impacts on wild pollinators, and to illustrate the use of expert elicitation methods as a useful tool to fill gaps where key data might be unavailable for the production of CFs for LCA.

4.2 Methods

4.2.1 Characterization model for land use impacts on pollinator abundance

To produce CFs, we applied a published model that characterizes land use impacts on pollinator abundance in a compatible way with LCA (Alejandre et al. 2022). The CFs are produced by estimating the difference in pollinator abundance associated with a given land use x (PA_x) in reference to the land type that is typically associated with the maximum number of pollinators per m^2 (PA_{ref}). The pollinator density associated with each land category is based on relative expert estimates (S_x), which are used to derive the CFs in reference to the most typically abundant land category (Alejandre et al. 2022) as follows:

$$CF_{O,x} = 1 - \frac{PA_x}{PA_{ref}} = 1 - \frac{S_x}{100}$$

The resulting CFs help translate land use inventory flows (specifically land 'occupation' flows as denoted in LCA terminology, in $m^2 \cdot year$) into relative pollinator abundance impacts. The indicator result, in this case the change in relative pollinator abundance for occupation impacts (PAO), is calculated by aggregating all occupation flows (O_x) after being multiplied by their respective characterization factors $(CF_{O,x})$:

$$Pollinator\ Abundance\ Occupation\ (PAO) = \sum_{x=1}^{x=n} \left(CF_{O,x} \times O_x\right)$$

where O_x is the time-integrated area of occupation in $m^2 \cdot year$. The unit of the indicator result PAO is also $m^2 \cdot year$. The indicator result can be interpreted as the impact on relative abundance of wild pollinators that is associated with the studied system. In the case of land use change (also referred in LCA as land transformation), CFs would be derived by estimating the difference in relative pollinator abundance between two different land use types and multiplied by a regeneration time according to UNEP-SETAC guidelines, to obtain compatible units that would allow for aggregation of land use impacts in LCA (Koellner et al. 2013; Milà i Canals et al. 2007). However, due to discrepancies in the operationalization of land 'transformation' impact assessment (Alejandre et al. 2022; Scherer et al. 2021), we focus in this study on the derivation of applicable CFs for land 'occupation' impacts, referred simply as land use.

4.2.2 Deriving pollinator abundance estimates (S_x)

To derive the pollinator abundance estimates associated with each of the land use types assessed and to determine a reference land use type, we conducted a Delphi assessment (described in detail in section 4.2.4). A Delphi assessment is an expert elicitation method that relies on iterative rounds where experts reconsider their scores based on intermediate rounds of feedback and argumentation (Hsu and Sandford 2007; Scolozzi, Morri, and Santolini 2012; Thangaratinam and Redman 2005). For this study, we consulted an international panel of 25 experts, covering 16 nationalities and with expertise across 45 countries (See Supporting Information A, Figure S1). The experts specialize in disciplines relevant to the topic of pollinators and pollination, some with first-hand experience conducting empirical field studies in different land-use types and agricultural crops, for different regions of the globe, and some with expertise in modelling relationships between land-use and pollinators. All participants remained anonymous to each other during the assessment to encourage equal participation and avoid overpowering dynamics. The assessment was carried out digitally through the Qualtrics survey software (www.qualtrics.com).

The participants were asked to provide relative estimates of wild pollinator abundance, by considering the foraging characteristics and nesting resources that can be typically associated with the land categories assessed, and to consider the potential influence of different land management practices. The relative scores were provided for a series of land use categories that were derived from the ecoinvent database (https://www.ecoinvent.org/) (see section 4.2.3). The categories were divided in three blocks (Described in detail in section 4.2.4). Block 1 consisted of the major aggregated land categories, and Blocks 2 and 3 of subgroups for Annual and Permanent crops respectively (Figure 4.1). Examples of the specific crops within each subgroup listed in ecoinvent were provided to the participants in the survey to be taken into consideration for their scores.

Throughout the three rounds of assessment, the feedback provided by experts on their argumentation for pollinator abundance estimates was used for interpretation of the scores and to help prevent and identify potential misunderstandings that could lead to false outliers. In case scores deviated significantly from the norm, the scores were corroborated with the written justification or direct contact with the expert to verify that the estimates were due to true dissent and not a result of potential misunderstanding. In the latter case, the scores provided by the expert were annulled from the entire round to avoid biases that could have been created by removing single values.

4.2.3 Selection of land use types to characterize

The land use categories assessed in this study were primarily derived from the ecoinvent life cycle inventory database. These comprise six main categories (Grassland, Forest, Permanent crops, Annual crops, Pasture, and Shrubland), listed for characterization in Block 1 (Figure 4.1). Additional subcategories of Annual and Permanent crops were assessed in Blocks 2 and Block 3 (Figure 4.1) for characterization and comparison. Crops that were identified by experts as misclassified during the first round of assessment (e.g., rapeseed originally classified as cereal), were corrected and assessed as separate categories during the third round of Delphi.

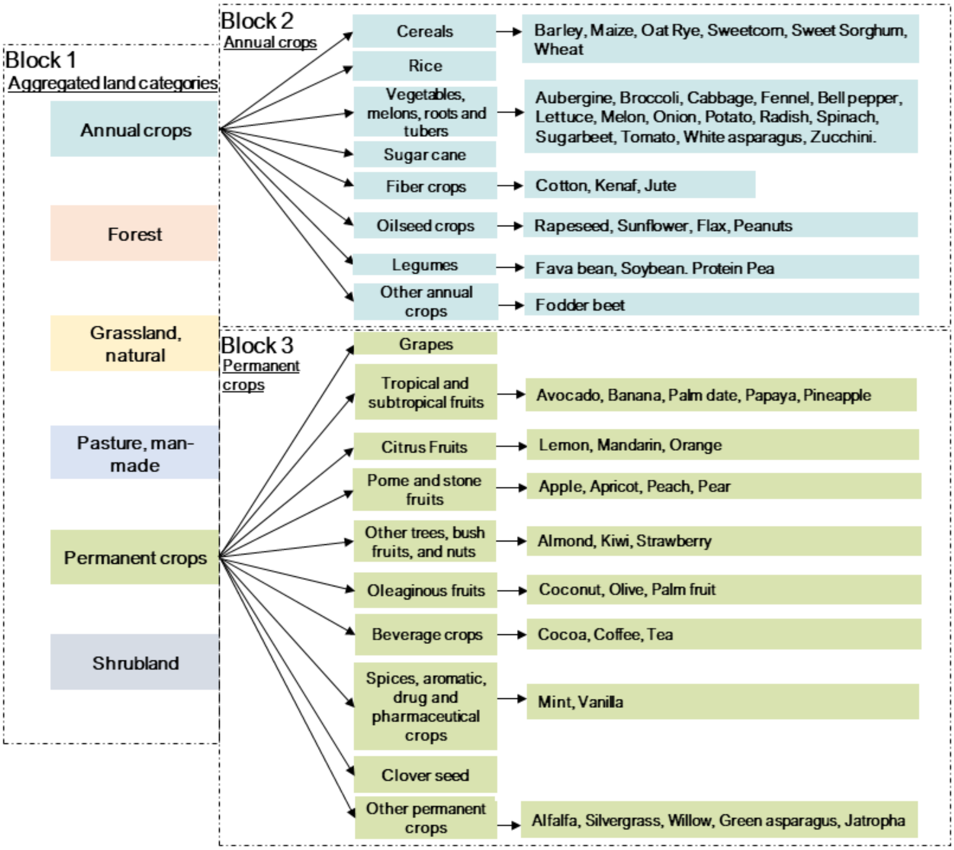


Figure 4.1 *Land use categories assessed for impact characterization. (For high resolution:https://pubs.acs.org/cms/10.1021/acs.est.2c05311/asset/images/large/es2c05311_0002.jpeg)*

4.2.4 Delphi assessment procedure

Experts were asked to provide pollinator abundance scores from 0 to 100, starting by assigning the maximum value to the category they considered as the reference (the one with the typically highest expected pollinator abundance) and then ranking the rest of the categories accordingly, assessing each block individually. The experts provided world-generic scores for the **typical** pollinator abundance ('typical' defined as the most expected or representative value, equivalent to the mathematical term 'mode'), as well as estimates for the **lowest** and **highest** pollinator abundance that could be associated with each land type by considering not only foraging and nesting resources but also the potential differences due to management practices and biogeographical variations. The participants provided a short, written justification or description of the considerations taken for each score (e.g., habitat characteristics, management practice considered or trends) and rated their confidence level for the typical estimates on a three-point Likert scale (Low, Moderate, or High). This estimation of confidence facilitated subsequent discussions by providing a basis of reference for the expertise of otherwise anonymous participants. These confidence scores served for interpretation and discussion of the results and were not used quantitatively.

At the end of each round, a statistical summary of the results (including mean and range of scores) was shared among the participants, along with an anonymous summary of the argumentations provided by the experts. The participants were asked to consider the argumentations for each category and resubmit their scores. At the end of the second round, the categories that did not reach consensus were submitted for a third and final round of evaluation. The consensus was measured through the coefficient of variation, estimated as the standard deviation divided by the mean and multiplied by a hundred. A coefficient of variation of ≤ 50 was considered as a threshold for consensus. The typical, low and high estimates were treated as independent values. At the end of the third round, the values that did not reach consensus were highlighted as not readily applicable without further evaluation.

4.2.5 Statistical processing of Delphi assessment results

The results of the Delphi assessment were used to derive the relative estimates of pollinator abundance for the calculation of CFs. In Block 1, the land category selected by most experts as the one expected to present, on average, the highest typical pollinator abundance, was treated as the reference land category. The typical values attributed by each participant to the reference land type were set to 100, and the rest of the values were scaled accordingly. In Blocks 2 and 3, experts provided estimates of abundance from 0-100 for subcategories of Annual and Permanent crops. These values were normalized by setting the maximum typical value provided by each participant as the normalized mean of the high abundance of Annual and Permanent crops in Block 1. For example, if the normalization of Block 1 results in a mean high abundance of 40 for Annual crops, the maximum typical estimates in Block 2 are set to 40 and the rest of the values are scaled. High abundance estimates can still result in values above 40 after scaling with the reference land. By normalizing Blocks 2 and 3 with the high abundance estimates, a wider range of pollinator abundance can be reflected for the subcategories of Annual and Permanent crops. This decreases potential bias from normalizing in reference to, for example, the mean of typical values only, or the average across typical, low and high estimates.

At the end of the Delphi assessment, the resulting normalized S_x estimates were converted to CFs for each land use category, applying the model described in section 4.2.1. The mean CFs for typical, low and high abundance are presented for each land use category, along with their standard deviation, which reflects the between expert uncertainty of the CF. Additionally, to reflect variations associated with, for example, both biogeographical and management differences, and for cases where it is not known if the typical, low or high abundance CF would be more appropriate, we combined all the typical, low and high CFs and calculated the standard deviation, resulting in the combined uncertainty for each land category. Lastly, given that the typical estimates represent, as its name denotes, the most typically expected abundance, we calculated the standard deviation of combining all the typical, low and high CFs, accounting for typical CFs twice, to provide a weighted uncertainty measure for each land use category.

4.3 Results

4.3.1 Pollinator abundance estimates

Based on the results of the Delphi assessment, natural Grassland was selected by most experts as the reference land type, with Shrubland as a close second. The estimates for the other land use types were treated relative to Grassland, and were scaled accordingly for each of the participants' estimates as described in section 2.5. All normalized S_x estimates are provided in the Supporting Information. In Block 1, the mean for typical abundance estimates ranged between values of 36 and 100, as presented in Figure S2 (Supporting Information A). Forest, Permanent crops and Pastures were rated with intermediate abundance estimates, while Annual crops was rated as the land use category presenting typically the lowest abundance. The mean low abundance estimates varied between 7 and 52 across land categories, and mean high estimates between 75 and 120. The largest range observed between the minimum and maximum values for typical and high abundance estimates in Block 1 occurs for the category of Forest.

A higher level of land use specificity was assessed in Block 2, covering subcategories of Annual crops. The estimates of Block 2 were normalized in reference to Grassland, based on the normalized high mean abundance estimate of 78.6 for Annual crops in Block 1. The normalized mean of S_x estimates for typical pollinator abundance vary between values of 9 and 76, while the mean of low estimates varies between 1 and 27, and for high boundaries between 29 and 116 (See Supporting Information A, Figure S3). Sugar cane and Rice were rated as crops with a typically low abundance, while the category Vegetables, melons, roots and tubers was rated by most experts as the most likely one to present a higher pollinator abundance, with a mean S_x value of 76. The typical estimate for Rice, Cereals and Other annual crops did not reach consensus (See Supporting Information A, Figure S4).

In Block 3, the subcategories of Permanent crops were normalized in reference to Grassland, assuming the mean normalized high abundance value of 93.11 in Block 1 as the maximum typical abundance in Block 3. The normalized mean estimates for a typical pollinator abundance vary between 30 and 88 across Permanent crops, while the values for mean low abundance estimates range between 8 and 51, and the mean high abundance estimated between 65 and 115 in reference to Grassland (Supporting Information A, Figure S5). All estimates for typical and high abundance rates reached consensus (Supporting Information A, Figure S4), and only five out of ten categories did not reach consensus for low abundance estimates. The category of Pome and stone fruits was rated as the most typically pollinator abundant category from Block 3, with a mean normalized value of 87.68.

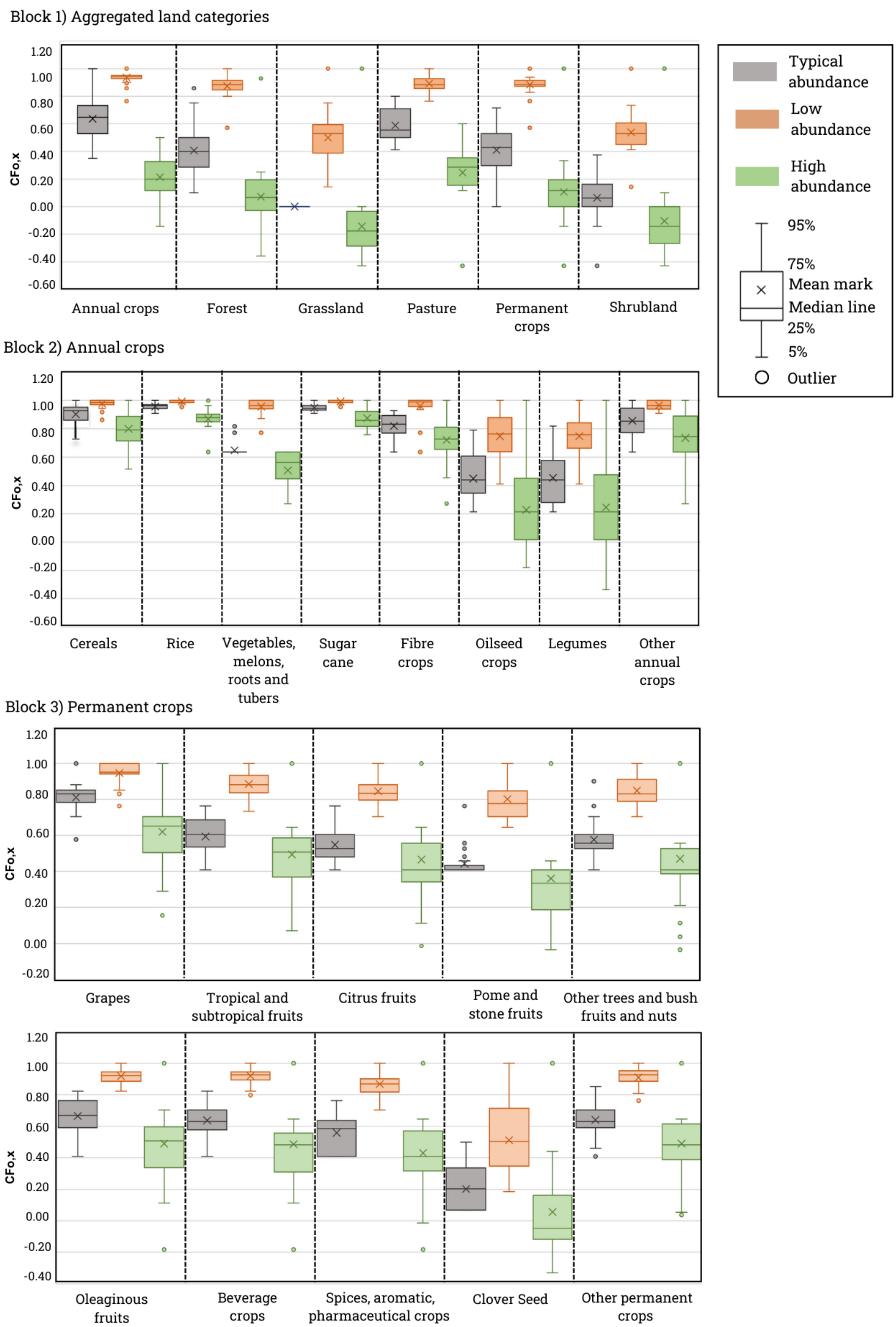
The initially high divergence observed for the typical abundance estimates for Rice, and the low abundance estimates for annual crops, forest and permanent crops decreased by almost half after three rounds (Supporting Information A, Figure S4). A coefficient of variation of ≤50% was not reached, but the results suggest that additional rounds of scoring and active argumentation could potentially lead to representative and convergent values for these categories. On the other hand, the low abundance estimates for categories such as Cereals, Rice, Sugar cane and Fibre crops presented a consistently high divergence across all three rounds of scoring, indicating dissent for those crops and/or lesser confidence in the case of Rice. Overall, increasing the level of specificity for the aggregated land use categories of Annual and Permanent crops (moving from Block 1 to Blocks 2 and 3) decreased the variability observed for these land use types, assessed as the range between low and high mean estimates. However, the confidence for the typical values provided for the aggregated Annual and Permanent crop categories in Block 1 is relatively high compared to the confidence in estimates for categories of Blocks 2 and 3 (Supporting Information A, Figure S6).

The few crops identified at the beginning of the assessment as misclassified, were corrected as Oilseed crops and Legumes in Block 2, and Clover seed in Block 3. Most of the abundance estimates for these categories showed a high consensus, with the sole exception of low abundance estimates for Oilseed crops. However, given that the estimates for these categories were the result of only one round of assessment, the resulting CFs are presented for illustrative purposes and are not recommended as readily applicable without further assessment.

4.3.2 Generic characterization factors for potential land use impacts on pollinator abundance

The pollinator abundance estimates from each expert were used to derive CFs for land occupation impacts, as described in section 4.2.1. The resulting CFs ($CF_{O,x}$) are presented in Figure 4.2 (full table of CFs can be seen in Supporting Information A, Table S1, along with combined and weighted uncertainty for each land use category, and further specification on CFs derived from estimates that did not reach consensus). The CFs are described as 'dimensionless', as they represent a given number of pollinators relative to the maximum abundance of a reference land ($m^2 \cdot year/\ m^2 \cdot \mathbf{year\ reference\ land}$, since land occupation flows are commonly expressed in LCA with the units $m^2 \cdot year$).

Figure 4.2 (In page 101) *Characterization factors for land occupation impacts on pollinator abundance (in $m^2 \cdot$ year/ $m^2 \cdot$ year of reference land) (For high resolution: https://pubs.acs.org/cms/10.1021/acs.est.2c05311/asset/images/large/es2c05311_0003.jpeg)* ❯


Block 1) Aggregated land categories
1.20
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
CFo,x
Annual crops
Forest
Grassland
Pasture
Permanent crops
Shrubland
Typical abundance
Low abundance
High abundance
95%
75%
Mean mark
Median line
25%
5%
Outlier
Block 2) Annual crops
Cereals
Rice
Vegetables, melons, roots and tubers
Sugar cane
Fibre crops
Oilseed crops
Legumes
Other annual crops
Block 3) Permanent crops
Grapes
Tropical and subtropical fruits
Citrus fruits
Pome and stone fruits
Other trees and bush fruits and nuts
Oleaginous fruits
Beverage crops
Spices, aromatic, pharmaceutical crops
Clover Seed
Other permanent crops

Experts provided short-written argumentations describing their considerations for each level of abundance along with their quantitative estimates. The main characteristics associated with low abundance estimates were non-flowering landscapes which present low foraging and nesting resources, as well as intensive, high chemical input, monoculture practices. High pollinator abundance estimates were generally associated with extensive management practices, low to no chemical input, rich understory and rich flowering plants. Given the detailed considerations made for each level of abundance and consistency in descriptions between experts, we recommend applying the low-abundance CFs to elementary flows that specify intensive practices, and the high-abundance CFs to elementary flows that describe extensive management practices. This aligns with recent efforts (Scherer et al. 2021) to provide guidance on the application of CFs and avoid arbitrary selection that can lead to deviating results. The CFs for typical estimates can be applied to generic flows where locations and management practices are unspecified (Figure 4.3). After normalization in reference to Grassland, estimates of high pollinator abundance above 100 resulted in negative CFs, reflecting positive impacts to pollinator abundance, which can be associated with land presenting exceptionally high quality of foraging and nesting resources, or under active restoration and maintenance practices. An indication of uncertainty for each CF is provided by a measure of dispersion, assessed, in this case, as the standard deviation.

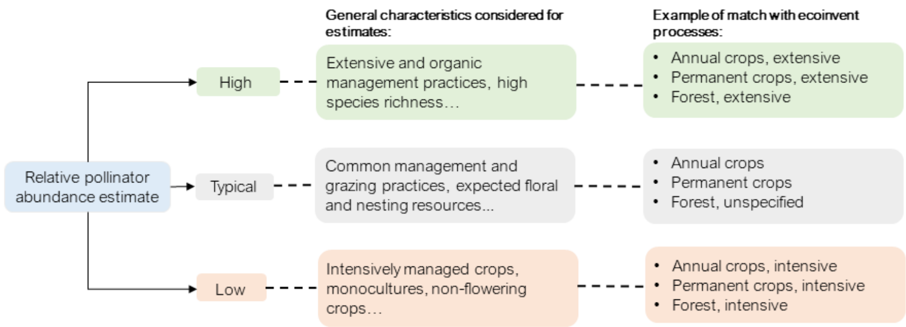


Figure 4.3 *Considerations by experts for pollinator abundance estimates and their compatibility with land use intensity levels found in the ecoinvent inventory. (For high resolution: https://pubs.acs.org/cms/10.1021/acs.est.2c05311/asset/images/large/es2c05311_0004.jpeg)*

4.4 Discussion

4.4.1 Considerations of expert elicitation assessment to characterize pollinator abundance

The use of a Delphi assessment for the derivation of comparable pollinator abundance estimates resulted in a comprehensive set of scores based on careful considerations from the experts involved in the assessment. This assessment allowed for the quantification of the potential impact on the relative pollinator abundance associated with diverse land use categories. Generally, the development of CFs requires simplifications and compromises to match the information available in life cycle inventories with the modelling of complex human-environment dynamics. In this case, the relationship between land use and pollinator relative abundance was assessed with the use of estimates based on expert knowledge and derived through a Delphi expert elicitation method. The Delphi assessment allowed us to quantify the relative differences in pollinator abundance associated with 24 land use categories, providing not only valuable data in terms of quantifiable estimates for characterization, but also recommendations that can be used for improvements of LCA databases and considerations in future studies.

The feedback provided by multiple experts, whose expertise combined cover an ample geographical scope, showed that their estimates were based on careful considerations regarding conventional practices and management of major crop types, as well as on variations that could emerge from seasonal and geographical differences. According to the argumentation submitted by the experts along with their scores, the type of management practices was one of the most influential factors for the variability of abundance not only within but also between crops. This reiterates the need to incorporate more detail regarding management practices at an elementary flow level by expanding the application of keywords such as “intensive” and “extensive” flows to most agricultural flows.

The relative pollinator abundance scores and thus CFs are consistent with trends observed in recent years regarding pollinator abundance. For example, annual crops, which are usually intensively managed, were linked in several studies to the lowest expected abundance and richness of pollinator communities (Bennett et al. 2014; Koh et al. 2016) while natural grasslands were commonly found to harbor the highest abundance rates (Pfiffner et al. 2018), helping increase species richness in comparison with annual crops (Bennett et al. 2014). However, it is important to notice that the method proposed in this study is based on averaged relative values and may not always be comparable to results from local measurements or predictions performed in a site-specific area(Blasi et al. 2021). Moreover, the high divergence observed for multiple low abundance estimates may highlight the need for further field and on-site research to verify the state of pollinator communities and allow for a better comparison of relative differences. While no confidence scores were provided for low and high estimates, the consistently high divergence of scores for low abundance estimates could indicate intrinsic regional and management variations, or a general lack of certainty and knowledge regarding the extent of pollinator abundance decrease in poor quality areas and intensively managed landscapes.

4.4.2 Dealing with uncertainty

When dealing with data derived from expert elicitation methods, there are generally three main sources of uncertainty. These are generally described as within-expert uncertainty, between-expert uncertainty and the uncertainty that can be attributed to data itself (for example, due to real heterogeneity (Blasi et al. 2021), misclassifications, etc.) (Czembor et al. 2011; Scolozzi, Morri, and Santolini 2012). Within-expert uncertainty occurs when an expert is unsure about the state or assessed quality of a particular land category (described as well as imperfect knowledge). To minimize within-expert uncertainty, participants were asked to submit their scores for up to 3 rounds and were encouraged to review the summary feedback. Additionally, experts provided a score of their confidence level for typical abundance estimates, which was used to interpret the variation in typical scores across rounds.

Between-expert uncertainty arises from disagreement among experts. The disagreements can be due to differences in, for example, expertise, heterogeneity of the land classifications, or cognitive biases (Czembor et al. 2011). To decrease between-expert uncertainty, the Delphi method relies on consecutive rounds of scoring where experts provide argumentation for their estimates which can then be considered by the other experts during their re-evaluation of scores. To decrease the risk of forced consensus that can arise from group dynamics, the participants were kept anonymous during the assessment, and everyone provided the survey results independently. The variation and convergence levels were assessed at the end of each round. As pointed out by the panel of experts, there was a handful of crops that were misclassified. These crops were separated into new categories and reassessed in the third round of the Delphi assessment.

To quantify the associated uncertainty of the pollinator abundance estimates produced in this study, we used a measure of dispersion, the standard deviation (*SD*). The CFs were produced for each land category and are presented along with their SD, as well as combined and weighted measures of uncertainty. Future studies could focus on the potential use of uncertainty measures to assess global sensitivity of the CFs and move towards regionalization of impacts to better reflect biogeographical differences (Cucurachi, Borgonovo, and Heijungs 2016).

4.4.3 Application in LCA and recommendations

The CFs for aggregated land categories assessed in Block 1 are directly applicable to the current elementary flow list of ecoinvent. To exemplify their application, we include a brief illustrative comparison of two hypothetical agricultural products (Supporting Information C), detailing the relevant inventory analysis and characterization of each product to assess the associated pollinator abundance decrease. The CFs for the more specific land use categories assessed in Blocks 2 and 3 can be selected based on unit processes within an inventory database.

While this study focused on the development of world-generic CFs for occupation impacts, pollinator communities and their capacity to provide pollination services are influenced by a range of biogeographical characteristics and agricultural land-use intensity that vary across the globe (IPBES 2016). To address these differences, country-specific CFs could be derived in future studies by matching the land use categories assessed in this study with land cover maps and/or land system archetypes to produce regionalized CFs that can represent the potential impact of occupying land in a given country or spatial unit chosen (Alejandre, Guinée, and van Bodegom 2022; Václavík et al. 2013). Furthermore, the geographies considered by the expert panel on their estimations of pollinator abundance cover 45 countries (See Supporting information A, Figure S1) from across all continents and representative biomes. However, additional input from experts on regions such as North and South Africa, as well as East Asia, could be the target of future efforts to improve the representativeness of the CFs.

While the derivation of CFs for transformation impacts were beyond the scope of this study, their assessment is essential to account for the impacts of land cover change (De Palma et al. 2016). However, current discrepancies in the operationalization of transformation impact assessment should be addressed in order to improve the compatibility of new CFs with inventory LCA flows and improve the accuracy of the assessment. From a pragmatic point of view, it would be recommendable and effective to provide CFs addressing a net transformation impact that can be directly linked to a single inventory flow (e.g., 'from annual to permanent crops'), instead of adjusting to the current structure where transformation flows are separated as two separate flows ('from' and 'to') (Scherer et al. 2021). The midpoint indicator result can be linked in future research to endpoint categories. For example, 'Ecosystem Quality' could reflect the relation between decreased pollinator abundance and potential decrease in plant species richness, while 'Human Health' could reflect malnutrition damages through agricultural productivity losses.

The inputs provided by experts indicate that protective land practices such as the maintenance or restoration of hedgerows and flower rich field margins can have a considerable influence on the expected pollinator abundance, even in crop areas where intensive management practices take place (Albrecht et al. 2020; Orford et al. 2016). Characterization factors for active restoration or enhancement activities can be included as negative CFs to represent their potential improvement on the expected pollinator abundance and allow for their consideration in the selection of land use practices when comparing among product systems. This is of significant value to support decision and policy making where analyses are made not only during design stages for the prevention of impacts but also to compare among remediation strategies where restoration measures are needed. Moreover, the high standard deviation in some of the land use categories assessed indicate the need to increase the level of detail provided in the elementary flows, as was the case for the category of Forest. Given the general consensus, dense, coniferous, monotypic, or intensively managed forests will likely support limited pollinator abundance in comparison with open, deciduous and tropical forests with understory vegetation. The inclusion of a few relevant keywords, such as the aforementioned, would better allow the differences within this category to be reflected.

4.5 Conclusion

The results of this study provide evidence of the applicability of expert elicitation methods to fill gaps where quantitative information might be missing from available sources for interdisciplinary applications such as impact assessment methods. This was further exemplified with the proven application of the resulting CFs in a hypothetical comparison between two crops, where key differences were observed on the pollinator abundance decline associated with each alternative. While the degree of pollinator abundance is of high relevance for its associated capacity to provide the ecosystem service of pollination, multiple other aspects remain as well of high concern, such as pollinator diversity and persistence of rare species. Future research could target the characterization of such additional environmental impacts, as well as the continuous improvement of the CFs produced in this study, with the aim to provide representative results that can aid prevent further declines of wild pollinators.

4.6 Supporting information

All supporting material is available online via:

Supporting information A:

https://pubs.acs.org/doi/suppl/10.1021/acs.est.2c05311/suppl_file/es2c05311_si_001.pdf

Supporting information B:
https://pubs.acs.org/doi/suppl/10.1021/acs.est.2c05311/suppl_file/es2c05311_si_002.xlsx

Supporting information C:
https://pubs.acs.org/doi/suppl/10.1021/acs.est.2c05311/suppl_file/es2c05311_si_003.xlsx

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Chapter 5

Assessing the use of land system archetypes to increase regional variability representation in country-specific characterization factors: a soil erosion case study

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Abstract

The characterization of land use impacts in life cycle assessment (LCA) requires a constant compromise between highly specific impacts models and coarse geographical scales available in life cycle inventory, where most information is provided at country level as the highest degree of geographical specificity. The derivation of country-specific characterization factors is usually done estimating impacts with the use of land cover and potential natural vegetation maps, assuming the most predominant biome per country as representative. This study explores the use of land system archetypes to derive country-specific characterization factors for land use-related soil erosion impacts that can better represent intra-national variations, while accounting for several biogeographical and socioeconomic differences. Land use-specific characterization factors were derived as the potentially enhanced soil erosion rate, using the soil erosion rates of each archetype as a reference state, and correction factors to reflect the relative increase or decrease in soil erosion rates associated with each of the eight land use types. Country-specific characterization factors for land use erosion impacts of occupation (in ton/(m^2·year)) were calculated by taking into account the land system archetypes present in each country, the land use-specific characterization factors, and the likelihood of each land use type occurring across archetypes (based on rule of thumb expert estimates). The country-specific characterization factors were produced specifically for occupation impacts for each of the eight land use types, and covering 263 countries and territories/dependencies. The resulting 2,104 country-specific characterization factors displayed in average a considerably greater variation in comparison with characterization factors produced when only the most predominant archetype per country is assumed as representative per country. The results indicate that world generic values might underestimate up to 10 times the degree of impacts associated with land use types such as permanent crops, fallow ground, mining, and landfill. The use of land system archetypes presents a viable approach to derive country-specific characterization factors while taking into account key intra-national variations, as well as biogeographical and socioeconomic factors.

Keywords: Life cycle assessment; Regionalization; Land use; Characterization

5.1 Introduction

The level of regionalization in life cycle assessment (LCA) for the estimation of land use impacts is commonly deter- mined by the available geographical scales found in life cycle inventory (LCI) databases, and the resolution of the characterization factors used to translate the inventory of a product system into potential impacts (Nordborg et al. 2017). Most LCI databases present information aggregated as either country-specific or world generic values (Wernet et al. 2016; Othoniel et al. 2016). Given the current structure and operationalization of LCA through its large-scale background databases, compatibility with available LCI scales is essen- tial to reflect the potential impact of background processes (those obtained from LCI databases, such as ecoinvent), since the application of high resolution characterization factors is usually limited to foreground processes (those createdby LCA practitioners) (Bos et al. 2020; Othoniel et al. 2019). LCA results are strongly influenced by background processes, as Heijungs (2012) showed by describing how the use of a single process from the ecoinvent database can be linked with ~2000 other processes. Background processes are commonly aggregated at country level as maximum degree of specificity (Yang 2016; Mutel et al. 2019; Pavan and Ometto 2016). Therefore, most regionalized impact methods that have been developed for LCA, such as LC- Impact (Verones et al. 2020), IMPACT world + (Bulle et al. 2019), and TRACI (Bare 2011), provide country-specific characterization factors. These country-specific estimates are usually obtained by utilizing land cover and potential natural vegetation (PNV) maps to characterize potential impacts, assuming the most predominant biome per country as a representative estimate for country-specific factors (Verones et al. 2020; Bulle et al. 2019; Saad et al. 2013; Bos et al. 2020). However, the estimation of country-specific values based on most predominant biomes per country might not accurately represent intra-national variation. Furthermore, land use impacts are influenced by a variety of factors that go beyond biogeographical characteristics, and that relate to socio-economic and environmental dynamics. In contrast with the general practices where the degree of land use impact is based on PNV land cover maps and biogeographical parameters, we hypothesize that land system archetypes can be used to increase representativeness of regional variations in the calculation of country-specific characterization factors.

The use of spatial archetypes has been proposed in the literature as a potential way towards regionalization of impact categories (Mutel et al. 2019). Archetypes, defined as groups or categories that share similar characteristics and patterns, can help incorporating information beyond spatial units. Moreover, land system archetypes can account for multiple factors, both socio-economical and biogeographical, that influence the degree of potential environmental impacts. An example of archetypes application in LCA is the case of the toxicity impact model, USEtox, which utilizes freshwater archetypes to assess the variability of impacts related to exposure to toxic substances and particulate matter (Gandhi et al. 2011; Rosenbaum et al. 2008; Kounina et al. 2014). Archetypes present potential advantages for application on several other impact categories, with land use as the clearest example of an impact driver that is highly dependent on multidimensional conditions varying across the globe (IPBES 2019). The objective of this study was to assess if the use of land system archetypes help to better represent intra-national variations when deriving country-specific characterization factors for soil erosion impacts as a representative example of land use-related impacts. Our focus was on illustrating the potential benefits of adopting land system archetypes for the derivation of characterization factors, rather than assessing or further developing a specific method for soil erosion impacts. By presenting the application and comparison of characterization factors based on land system archetypes, we provide further evidence of their potential benefits for a wider application in LCA studies and a better representation of socio-economical and biogeographical differences across the globe.

5.2 Methods

5.2.1 Land system archetypes

In this study, 12 land system archetypes (LSAs) produced by Václavík et al. (2013) were used for the characterization of land use impacts. These archetypes are based on clustered patterns of land systems data, covering approximately 30 indicators related to land use intensity (e.g., soil erosion, irrigation, temporal trends of cropland), socioeconomic factors (e.g. population density, GDP), and environmental factors (e.g., temperature, precipitation) (Václavík et al. 2013). Each of the 12 LSAs presents a specific combination of land use and human–environment interactions. We used the soil erosion rates that are associated with each of the 12 land system archetypes as the reference state (Qref,a) to assess land use-related soil erosion impacts (further explained in Sect. 5.2.2). These soil erosion rates (see Table 5.1) have been derived from spatially explicit models of soil erosion based on the universal soil loss equation, and used in conjunction with global databases of land use, soil, climate, accounting for parameters such as slope steepness and soil organic carbon (Van Oost et al. 2007). For further clarification, throughout this study, we refer to the terms “land system archetypes” and “land use types.” The first one refers to the 12 archetypes produced by Václavík et al. (2013), while land use types refer to the specific use of land that can have an erosion impact on the studied land (e.g., agricultural crops, natural landscape, roads). Therefore, one or multiple land use types can take place in a land system archetype (e.g., a road through a forest system in the tropics).

Table 5.1 *Soil erosion rates associated with each of the land system archetypes by Václavík et al. (2013).*

	Land system archetype	Soil erosion rate (in ton/(ha·year))
LSA 1	Forest systems in the tropics	2.6
LSA 2	Degraded forest/cropland systems in the tropics	120.3
LSA 3	Boreal systems of the western world	0.2
LSA 4	Boreal systems of the eastern world	0.1
LSA 5	High density urban agglomeration	3.1
LSA 6	Irrigated cropping systems with rice yield gap	6.2
LSA 7	Extensive cropping systems	5.9
LSA 8	Pastoral systems	1.8
LSA 9	Irrigated cropping systems	2.4
LSA 10	Intensive cropping systems	2.8
LSA 11	Marginal lands in the developed world	0.7
LSA 12	Barren lands in the developing world	0.3

5.2.2 Determination of land use-specific characterization factors

Before deriving country-specific characterization factors, we first calculated land use specific characterization factors. Land use specific characterization factors were calculated as the potentially enhanced land use-specific soil erosion rate ($CF_{a,b}$) expressed in ton/(m^2·year), which describes the potential soil erosion impact of land use b on archetype a, calculated as the difference in soil erosion rates between the reference state ($Q_{ref,a}$) and the state under the given land use b ($Q_{LU,a,b}$).

$$CF_{a,b} = Q_{\ LU,a,b} - Q_{ref,a}$$

Where $Q_{ref,a}$ is the soil erosion rate of archetype a, and $Q_{LU,a,b}$ is the soil erosion rate associated with land use b, calculated by multiplying the soil erosion rate of archetype a ($Q_{ref,a}$), by a 'correction factor' of land use type b ($K_{use,b}$) that is adapted from the LANCA method by Beck et al. (2010) (Figure 5.1). Thus:

$$Q_{LU,a,b} = Q_{ref,a} * K_{use,b}$$

These 'correction factors' (K_{use}) reflect the relative degree of soil erosion impact that can be attributed to each land use type. The factors are dimensionless numbers ranging from 0.5 to 10, and available for 36 land use types (Beck et al., 2010). These correction factors represent a considerable simplification of soil erosion mechanisms. While alternative approaches have utilized additional correction factors to incorporate relative differences due not only to land cover but also management practices, for the comparative and illustrative purposes of this study, we assume the correction factor K_{use} from Beck et al. (2010) as an applicable approximation to estimate land use-specific soil erosion rates.

The specific land use types to assess in this study were selected based on their compatibility with land use elementary flows used in background processes of the ecoinvent database (https://www.ecoinvent.org/), given that this is one of the most predominantly used database in the LCA field (Wernet et al. 2016). To select the land use types, we compared the list of land use types for which Beck et al. provides K_{use} factors, with the detailed list of relevant background processes in ecoinvent (Version 3.4, 'cut off'). This comparison (detailed in Supporting information) led to the following selection of land use types assessed in this study: 'Forest', 'Permanent crops, 'Farmland', 'Fallow ground', 'Urban, industrial and transport', 'Grassland, meadow', 'Moorland, lawn or fallow with vegetation', and 'Mining and landfill'.

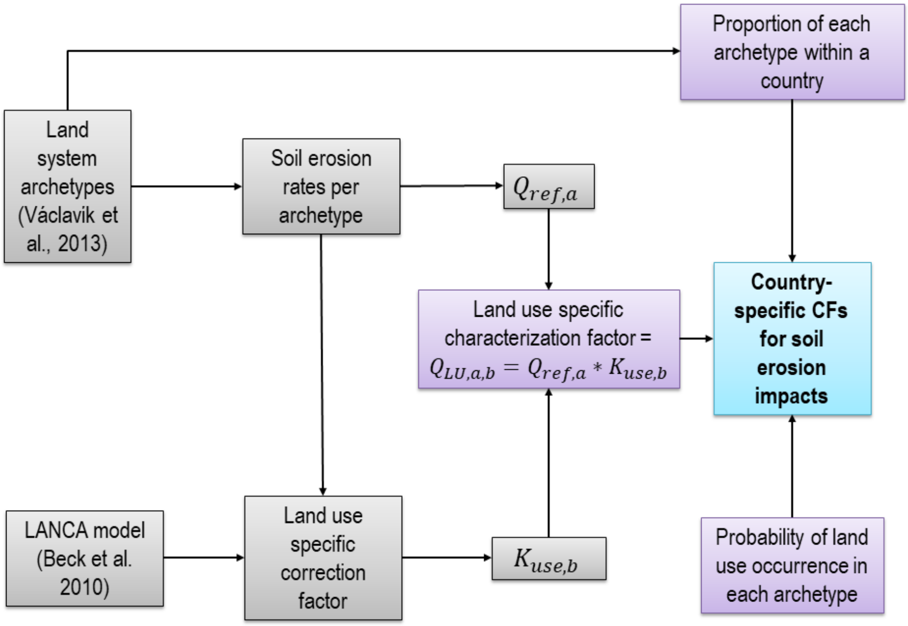

Figure 5.1 *Study design for the calculation of country-specific characterization factors for land use soil erosion impacts*

Furthermore, the characterization of land use impacts is commonly done for two types of impacts, occupation and transformation. Occupation describes the influence of land use over an area for a given amount of time ($CF_{occ} = Q_{ref} - Q_{LU}$) while transformation is described as the change in quality of an area from one land use to another, including the regeneration time ($CF_{trans} = (Q_{ref} - Q_{LU})*0.5*t_{reg}$) (Koellner et al. 2013; Milà i Canals et al. 2007). If the same ΔQ is incorrectly assumed to be applicable to the calculation of CFs for both occupation and transformation impacts, there is a risk of incurring on double counting during the impact assessment of a product system. Additionally, most land use processes in ecoinvent were found to have the same magnitude of flows for both occupation and transformation (see examples in Supporting information). While land occupation always follows land transformation, the reverse is not always the case. Therefore, the current connection of flows inevitably increases the risk of incorrect double counting. Based on these considerations and for the comparative purposes of this study, we will illustrate the production of characterization factors focusing on occupation impacts only.

As an additional consideration for the case of sealed soils, which occur in roads, industrial and urban areas for example, the procedure by Beck et al. (2010) assigns a high erosion correction factor to represent the permanent damage done to the quality of soil. However, for land use **occupation** impacts, the soil erosion is neither improved nor decreased by the effect of sealing. While sealing has a negative effect on other soil properties such as mechanical and physicochemical filtration (Beck et al., 2020), the soil erosion is not actively increasing nor decreasing due to the sealing during occupation impacts. To address this methodological artifact, we attribute the neutral value of 1 as the correction factor K_{use} for sealed soils corresponding to urban/industrial/transport land use types, this results in a characterization factor of value 0, representing no change of erosion during occupation. The impact of soil sealing would be reflected as a transformation impact. However, the production of CFs for transformation impacts are currently left of out of the scope of this study. For the land use types of mining and landfill, the maximum value of 10 was used as K_{use} factors for occupation impacts.

5.2.3 Producing country specific characterization factors

To aggregate towards country-specific characterization factors for each land use type, we produced characterization factors for occupation impacts for each land use type, e.g. *b*, in country *c* ($CF_{OCC,b,c}$) based on a weighting process taking into account the impact potential of land use type *b* on each archetype present in country *c* ($CF_{a,b,c}$), the probability of the land use *b* occurring on each archetype present in country *c* ($PO_{a,b,c}$), and the area of each archetype *a* within a country *c* ($Ar_{a,c}$), which results in:

$$CF_{OCC,b,c} = \frac{\sum_{a=1}^{12}(Ar_{a,c})(CF_{a,b,c})(PO_{a,b,c})}{\sum_{a=1}^{12} Ar_{a,c}}$$

For example, the probability of using the land as ‘Forest’ is considered to be minimal in archetypes such as LSA5 (High density urban agglomeration) and LSA12 (Barren lands in the developing world), and quite high in archetypes such as LSA1 (Forest systems in the tropics) and LSA3 (Boreal systems of the western world). These probabilities estimates ranged between three values (0.1, 0.5 and 1), and were based on rule of thumb expert estimations (see Supporting information).

5.2.4 The indicator result

Characterization factors are used to translate environmental interventions into potential environmental impacts, commonly referred to in LCA as the indicator results. The characterization factors produced, translate occupation flows for land use type b in country c $(O_{b,c})$ into potential soil erosion impacts by multiplying the land use flows by their respective characterization factors $(CF_{Occ,b,c})$. The impact results are aggregated across all land use types into an indicator result:

$$Soil\ Erosion\ Occupation\ (SEO) = \sum_{x=1}^{x=n} \left(CF_{Occ,b,c} \times O_{b,c}\right)$$

The impact indicator, which in LCA refers to the quantifiable representation of an impact, corresponds to the tons of soil eroded due to land use impacts. Where $O_{b,c}$ is the time-integrated area of occupation (in $m^2 \cdot$year). The unit of the estimated impact, the indicator result (SEO) is thus in tons, which represents the tons of soil eroded that can be associated with the functional unit of a studied system.

5.3 Results

5.3.1 Land use-specific characterization factors

The land use-specific impacts on soil erosion rates were characterized for each combination of land use and archetype, presented in Table 5.2. For the categories "moorland" and "Urban and industrial," the land use-specific characterization factors (in ton/(m^2·year)) result in values of 0, due to the fact that the correction factors had a value of 1, indicating that these land use type do not increase or decrease soil erosion. The land use-specific characterization factors for the categories grassland and forest have negative values, which indicate a reduction in soil erosion across all archetypes. The categories of permanent crops, farmland, and fallow ground present positive values, indicating a negative impact to the soil by increasing erosion rates. The values of these land use-specific impacts vary across archetypes, with LSA2 (degraded forest/cropland systems in the tropics) being disproportionally higher than the rest, due to the fact that this archetype is present in areas of the world characterized with the highest soil erosion rate (Table 5.1).

Table 5.2 *Land use specific characterization factors (in ton/(m^2·year)), for each combination of land use type and land system archetype*

		Land use type							
Land system archetype		Grassland	Forest	Farmland	Fallow ground	Permanent crops	Mining/Landfill	Urban/ Industrial	Moorland
LSA 1	Forest systems in the tropics	-1.30E-04	-1.30E-04	5.20E-04	2.34E-03	1.30E-03	2.34E-03	0	0
LSA 2	Degraded forest/cropland systems in the tropics	-6.02E-03	-6.02E-03	2.41E-02	1.08E-01	6.02E-02	1.08E-01	0	0
LSA 3	Boreal systems of the western world	-1.00E-05	-1.00E-05	4.00E-05	1.80E-04	1.00E-04	1.80E-04	0	0
LSA 4	Boreal systems of the eastern world	-5.00E-06	-5.00E-06	2.00E-05	9.00E-05	5.00E-05	9.00E-05	0	0
LSA 5	High-density urban agglomerations	-1.55E-04	-1.55E-04	6.20E-04	2.79E-03	1.55E-03	2.79E-03	0	0
LSA 6	Irrigated cropping systems with rice yield gap	-3.10E-04	-3.10E-04	1.24E-03	5.58E-03	3.10E-03	5.58E-03	0	0
LSA 7	Extensive cropping systems	-2.95E-04	-2.95E-04	1.18E-03	5.31E-03	2.95E-03	5.31E-03	0	0
LSA 8	Pastoral systems	-9.00E-05	-9.00E-05	3.60E-04	1.62E-03	9.00E-04	1.62E-03	0	0
LSA 9	Irrigated cropping systems	-1.20E-04	-1.20E-04	4.80E-04	2.16E-03	1.20E-03	2.16E-03	0	0
LSA 10	Intensive cropping systems	-1.40E-04	-1.40E-04	5.60E-04	2.52E-03	1.40E-03	2.52E-03	0	0
LSA 11	Marginal lands in the developed world	-3.50E-05	-3.50E-05	1.40E-04	6.30E-04	3.50E-04	6.30E-04	0	0
LSA 12	Barren lands in the developing world	-1.50E-05	-1.50E-05	6.00E-05	2.70E-04	1.50E-04	2.70E-04	0	0

5.3.2 Country-specific characterization factors

The characterization factors were derived for 263 countries and for 8 land use types, resulting in 2,104 values expressed in terms of ton/(m^2·year) (data generated and full list of CFs available in Supporting information). The country-specific characterization factors allow to distinguish between land use types, and present a wide range of variation for permanent crops, fallow ground, and mining and landfill, with mean values around 0.002ton/(m^2·year), and reaching max values, including outliers, of up to 0.035ton/(m^2·year) (Figs. 5.2a and 5.3). To compare the CFs, we also calculated country-specific characterization factors based only on the most predominant archetype per country (and without applying probability of occurrence factors) (Fig. 5.2b).

The CFs based on the most predominant archetype per country ranged between 0 and 0.003ton/(m^2·year) for permanent crops and between 0 and 0.005 ton/(m^2·year) for fallow ground and Mining landfill, indicating these CFs could underestimate impacts of up to 0.020ton/(m^2·year) for permanent crops and of up to 0.035 ton/(m^2·year) for fallow ground and mining and landfill. The benefits of grassland are underestimated as well when only accounting for the most predominant archetype in comparison to CFs weighting all archetypes within a country, with a difference of $6.26*10^{-4}$ ton/(m^2·year). Similarly, for forest, the mean CFs indicate lower benefits in comparison to weighted values. However, these CFs have a slightly larger range (from 0 to -0.0031) than weighted values (0 to -0.00022), due to the influence of the probability of occurrence estimates.

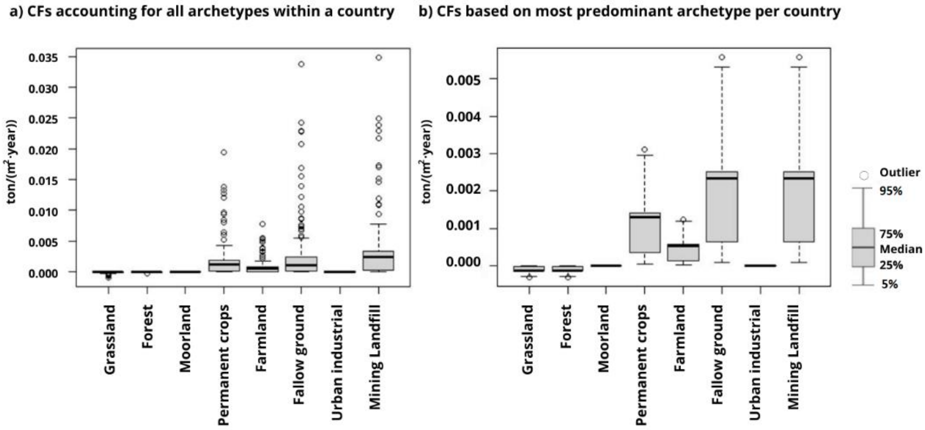

Figure 5.2 *Country-specific characterization factors for soil erosion potential impacts (in ton/(m²·year)).*

Furthermore, when accounting only for the most predominant archetype per country, not all archetypes are represented in the CF results. This was the case for LSA 2 (degraded forest/cropland systems in the tropics) and LSA 5 (High density urban agglomerations), which are not predominant in any country. Considering the high soil erosion rate and impact potential associated with LSA2 (Table 5.2), the use of country-specific CFs based only on most predominant archetypes as reference does not allow to reflect key land use impacts on highly vulnerable areas. The countries characterized as some of the most vulnerable in terms of soil erosion impacts for permanent crops, farmland, and fallow ground (e.g., Rwanda, Guatemala, Philippines, Swaziland, New Zealand, Malaysia, Burundi, Sri Lanka, Albania, and Dominican Republic) present as common feature an archetype composition mainly dominated by a combination of LSA1 (forest systems in the tropics), LSA2 (degraded forest/ cropland systems in the topics) and LSA7 (Extensive cropping systems). Therefore, the use of weighted values for the production of characterization factors results in a more comprehensive representation of intra-national impacts.

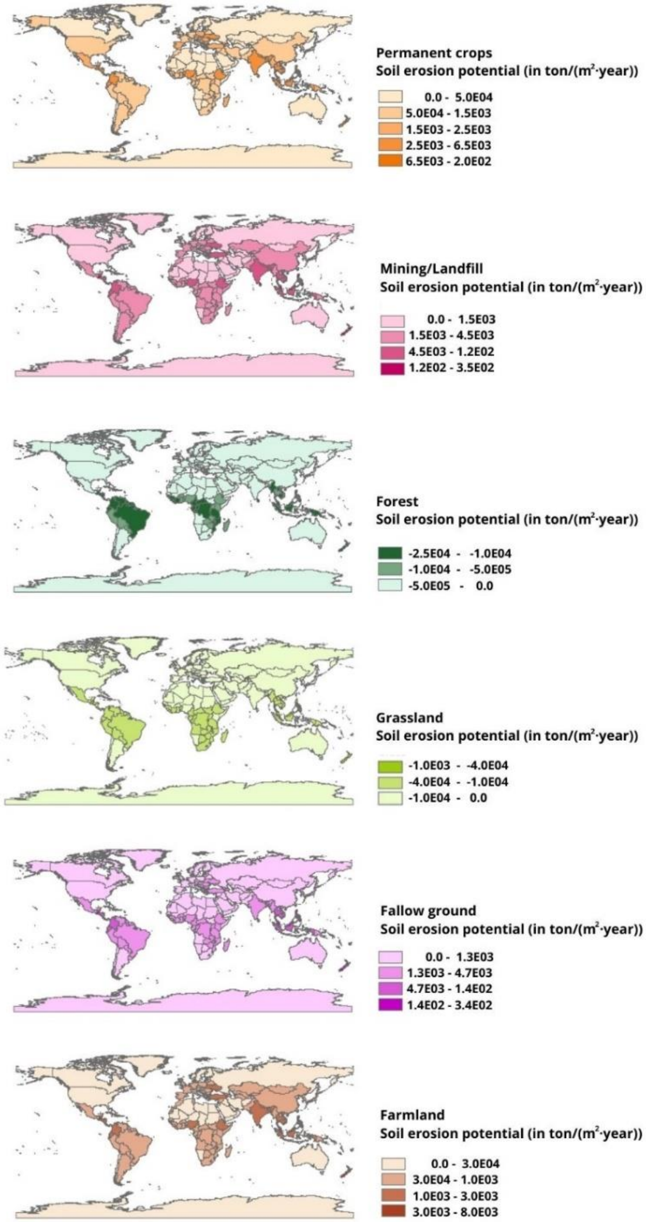

Figure 5.3 *Global maps of country-specific characterization factors for soil erosion potential impacts by land use occupation (in ton/(m^2·year)).*

The probabilities of land use occurrence (PO) were rule of thumb expert estimates (of value 0.1, 0.5, and 1) based on the assumption that not all land use types have the same probability of occurring across all archetypes. To assess the influence of these probability estimates, we compared the results with CFs produced without taking into account the probability estimates (assuming PO = 1 across all land types and archetypes). The results of this comparison (Fig. 5.4) indicate that the use of probability estimates allow to identify differences between grassland and forest, which would otherwise be represented by the same values, given that both land use types use the same correction factor of 0.5. The mean benefits of grassland and forest are slightly decreased by the use of the probability estimates. The variation range is also smaller, due to the fact that we assumed a low probability (= 0.1) of these natural landscapes occurring in archetypes describing urban or highly agglomerated areas.

By taking into account the occurrence probabilities, the potential bias due to unlikely combinations is decreased. For example, while grassland represents the highest potential benefits when assessed for LSA2 (Table 5.2), the probability of grassland occurring in LSA2 was attributed a probability estimate of 0.5, thus decreasing the influence of LSA2 in the total CFs for grassland by half. For farmland, permanent crops, and mining and landfill, there were no substantial differences between the results, while the mean impacts for fallow ground are slightly increased when no probability of occurrence is assumed. Furthermore, a comparison of CFs obtained with world generic estimates based on the mean of each land use type (Fig. 5.5) shows that world generic estimates can underestimate over ten times the degree of potential impact associated with land use types such as mining and landfill, fallow ground, and permanent crops.

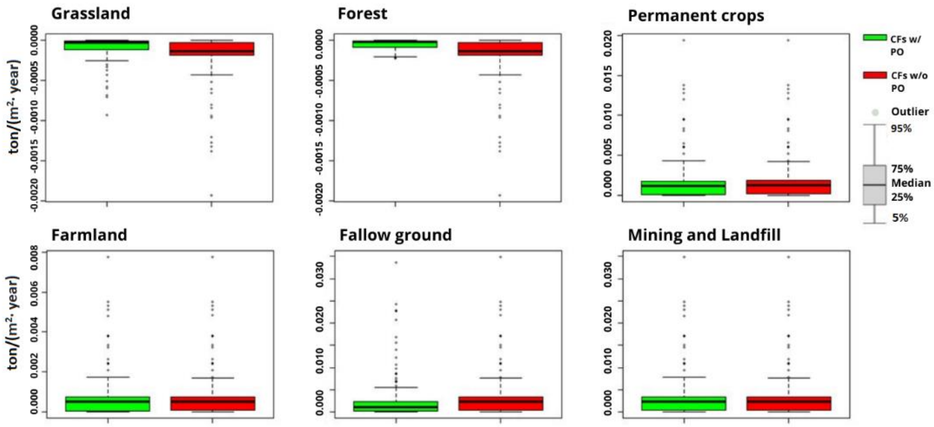

Figure 5.4 *Comparison of the resulting characterization factors when accounting for probability of occurrence estimates (in green) and without (in red).*

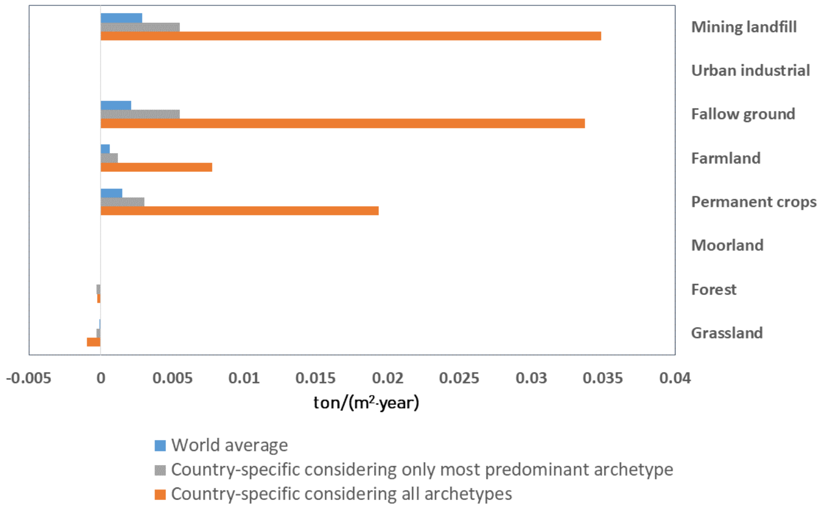

Figure 5.5 *Comparison of the characterization factors values for world generic (blue), country- specific considering only most predominant biome (grey), and considering all archetypes within a country (orange).*

5.4 Discussion

5.4.1 Considerations for country-specific characterization factors

The compatibility of characterization factors with the information present in LCA inventory databases is, as previously mentioned, generally a limiting factor to the applicability of new regionalized impact methods that need to reconcile with coarse geographical scales available in inventory data. In the case of land use impacts, this reconciliation generally leads to the production of country-specific characterization factors that are commonly derived by considering the most predominant biome per country as representative of the whole. While moving from world generic estimates to country-specific values might seem like a sufficient compromise, the great variation shown by the resulting characterization factors demonstrate further evidence of the need to improve the representation of intra-national variations during impact characterization, as illustrated in this study with the use of land system archetypes.

Furthermore, the use of occurrence probabilities in the calculation of characterization factors allowed us to evaluate additional differences between land use impacts by taking into account the characteristics of each land system archetype. The risk of potentially underestimating benefits or potential impacts will depend on the assumptions made for each occurrence probability. This risk may be reduced by obtaining occurrence probabilities based on a wider consensus of expert knowledge, or by coupling land use and urban planning data for more accurate predictions. We suggest that using coarse probability estimates might be better than using none, as further evidenced when comparing our results with those from Saad et al. (2013), where the characterization factors for grassland and forest present the same values and are therefore unable to reflect differences between these two land use types, a shortcoming that can be overcome with the use of occurrence probabilities.

5.4.2 Advantages of land system archetypes

The land system archetypes used in this study were produced by Václavík et al. (2013) using a self-organized map (SOM), which relies on a non-supervised neural network algorithm that decreases dimensionality by eliminating redundancy among indicators and allowing to visualize complex datasets. The output is a map where a given amount of archetypes is determined to be a representative amount of categories to represent land use systems (Václavík et al. 2013). The resulting archetypes reflect patterns clustered in consistent groups based on the similarity of the available indicators. There are several potential benefits of utilizing unsupervised data driven methods to further develop archetypes that can be used for impact characterization, as they allow to cluster large amount of data without the need of expert rules or a priori classification thresholds. The archetypes by Václavík et al. (2013), reflect regional patterns that take into account several land use intensity indicators and temporal trends to account for changing dynamics of land systems, and therefore might be better suited to reflect land use potential impacts in contrast with estimates based solely on land cover maps where only a few biogeographical parameters are considered. For example, while CFs for soil erosion impacts are usually heavily influenced by soil texture and geographical slope data, the land system archetypes that were particularly vulnerable to further soil damage were characterized by factors such as a high degree of agricultural inputs, low GDP and strong dependence on agricultural production (Václavík et al. 2013). Therefore, accounting for socio-economic factors besides biogeographical parameters seems indispensable to improve representativeness of characterization factors for land use impacts.

5.4.3 General recommendations for LCA application

For a practical application of archetypes in LCA, it is recommendable to apply or develop an archetype classification that can be used across several impact categories, to keep consistency and minimize the proliferation of category-specific archetypes (Mutel et al. 2019). The land system archetypes used in this study, by Václavík et al. (2013), account for a variety of parameters such as crop yield, fertilizer input, species richness, irrigation, among several other factors that present opportunities for their use in other impact categories. However, this should be further studied by for example, a meta-analysis focusing on the different data requirements across categories. Further integration of environmental and socioeconomic indicators with the use of archetypes presents potential advantages for the characterization of environmental impacts in LCA and in particular of ecosystem services. Ecosystem services have gained attention during the last decade due to their key role sustaining quality of life throughout the world (EEA 2016; FAO 2015; IPBES 2019). The severe degree of anthropogenic impact found across several key services globally, has fuelled increased efforts for their incorporation in impact assessment methods (Blanco et al. 2017; Zhang et al. 2010, Beck et al. 2010; Bos et al. 2016; Mutel et al. 2019; Cao et al. 2015; Milà i Canals et al. 2007a; Núñez et al. 2013; Othoniel et al. 2019). However, their assessment still remains highly underrepresented in common LCA studies (Othoniel et al. 2016; Alejandre et al. 2019).

The complex dynamics that influence ecosystem services and their high spatial variability present multiple characterization challenges. The archetypes approach outlined in this study is highly suitable to address these issues, precisely for its capacity to incorporate a range of multidimensional aspects while allowing to characterize impacts for LCA. Additionally, while general recommendations have been made in the literature regarding uncertainty (Igos et al. 2019; Muller et al. 2016), assessing and merging the several sources of uncertainty associated with characterization factors presents major challenges for impact assessment developers (Mutel et al. 2019). In the case of the land system archetypes, the nature of the data and methods applied to produce the resulting archetype classification introduces several levels of uncertainty. Additional uncertainty sources for the characterization factors are related with the characterization model assumptions, inherent spatial variability, among others. To include an estimate of uncertainty for regionalized CFs, developers usually provide measures of dispersion along with their resulting CFs to reflect the uncertainty associated with the spatial variability, for example, by estimating the average absolute deviation to show how far is a CF from the central tendency (e.g., median value). However, further research is necessary to determine the best approach for harmonizing uncertainty guidelines for both LCI databases and impact assessment developers.

5.5 Conclusions

The results of this study illustrate how the use of land system archetypes present a practical and representative approach to characterize land use impacts while accounting for intra-national differences in country-specific CFs. The hypothesis was that by utilizing land system archetypes we could better reflect spatial variability that can be driven by biogeographical and socioeconomic factors, than by simply assessing the most predominant archetype as the representative per country. This was confirmed by the comparison of country-specific CFs, which presented a considerably larger variation when accounting through a weighting process all the archetypes present within a country, than those assuming only the most predominant archetype as representative. The resulting CFs yielded estimates of up to ten times higher magnitude compared with world generic values, reflecting considerable regional differences. Moreover, our use of land system archetypes as reference state avoided potential biases in impacts of land use change, as it accounts for prevailing general soil degradation – in contrast to the commonly used potential natural vegetation as reference state. A wider application of archetypes for regionalization of impacts in LCA is recommended for further research as a practical approach to bridge the gap between impact models that require finer spatial and multidimensional data with currently available LCA inventories.

5.6 Supporting information

All supporting material is available online via:

https://static-content.springer.com/esm/art%3A10.1007%2Fs11367-022-02037-w/MediaObjects/11367_2022_2037_MOESM1_ESM.docx

https://static-content.springer.com/esm/art%3A10.1007%2Fs11367-022-02037-w/MediaObjects/11367_2022_2037_MOESM2_ESM.xlsx

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Chapter 6

General Discussion

The aim of this thesis was to investigate whether and to what extent we can incorporate the assessment of ecosystem services in LCA studies. In particular, I investigated if existing ecosystem service methods could be compatible with the impact assessment phase of LCA, and to propose approaches for the development of characterization factors (CFs) that can aid on the implementation of new impact categories that are directly linked to ecosystem services. In this chapter I discuss the findings for each of the research questions addressed in this thesis, starting in section 6.1.1 with an overview of the ecosystem services already included in impact assessment methods and the identified gap towards a proposed optimal coverage (RQ1). Aiming for a way forward, I discuss in section 6.1.2 a new impact category proposed to assess one of the ecosystem services identified as missing, and the considerations taken to reconcile differences between existing ecosystem service methods, the impact assessment phase of LCA and available LCI data (RQ2). While our approach is applied to characterize the influence of land use impacts on pollinator abundance, the recommendations derived can be applied to other ecosystem services that present similar characteristics.

Two main challenges for the development and successful incorporation of ecosystem service assessment in LCA were addressed in this thesis. Firstly, the compatibility of the CFs with LCI data, which can facilitate or hinder their applicability (RQ3), and secondly, the representation of biogeographical and socioeconomic variation that is relevant for ecosystem services, within country-specific CFs (RQ4). Addressing the first, the advantages of expert elicitation methods to tackle key data gaps are discussed in section 6.1.3, along with valuable insights retrieved from the stablished interdisciplinary collaboration (**Chapter 4**). In section 6.1.4, the use of Land System Archetypes (LSAs) is discussed as a viable approach to incorporate both biogeographical and socioeconomic parameters during the development of characterization factors, illustrated with the case of land use impacts on soil erosion. Lastly, limitations on the current characterization of land use impacts are discussed in section 6.2.1, followed by reflections on the societal relevance of improving the assessment of ecosystem services and other key environmental impacts in LCA studies (section 6.2.2).

6.1 Bridging the gap

6.1.1 Ecosystem services in LCA: where are we now?

For the determination of the current state of ecosystem services in LCAs and to present an overview of the results achieved by previous studies, the first step of this thesis was to conduct a review and analysis of ecosystem services found within current impact categories. While some of the previous studies had focused on developing recommendations for future integration of ecosystem service assessment, none had presented an overview of those already covered and/or linked with commonly used impact assessment methods. To achieve this, we investigated the impact assessment family 'ReCiPe2016', and found that multiple ecosystem services can be considered to be directly and indirectly assessed through a handful of impact categories, providing further evidence that the assessment of ecosystem services is operationally compatible with current LCA practices. This is exemplified by the multiple midpoint impact categories assessing the availability and provision of resources such as water, minerals and fossil resources. In the case of water use, the effect of this impact on ecosystem services is assessed further to the Area of Protection 'Ecosystem quality', through endpoint damage pathways that estimates the potential reduction of net primary productivity and plant diversity.

The CICES categories of ecosystem services that were deemed as compatible for environmental LCA were summarized in Chapter 2. From this inventory, we found that approximately 4 overarching categories are completely missing from both LCAs and from the literature proposing concrete indicators for the inclusion of ecosystem services in LCA. Examples of such ecosystem services are the provision of genetic resources, as well as the regulation and maintenance of pest and disease control. Given the high diversity of ecosystem services, there are major challenges for the development of a generalized framework that can encompass all missing categories. However, a practical approach as recommended by this thesis, is to focus on key ecological features and processes that can be found close within the cause-effect impact pathway of an ecosystem service. This can facilitate the development of CFs for midpoint and/or endpoint indicators, allowing to incorporate new impact categories that can be directly linked to ecosystem services.

Focusing on the impact assessment phase and in particular on the development of characterization factors, aligns with efforts by previous studies (de Baan et al. 2013; Beck et al. 2010; Saad, Koellner, and Margni 2013) and those listed in Figure 6.1. An approximate amount of seven overarching ecosystem services categories have been addressed by previous studies proposing midpoint indicators. However, the proposed impact categories had not yet been included in families of impact assessment methods such as ReCiPe2016. Alternative approaches as the ones proposed by Blanco et al. (2017), who targeted the incorporation of ecosystem services through inventory flows, and Cao et al. (2015) who focused on the development of weighted endpoint indicators, exemplify the diversity of approaches that can be considered, providing promising opportunities to increase the number of ecosystem services that could be represented in LCA studies. However, a wide application of any of the proposed methods is dependent on the actual incorporation of the relevant inventory data and CFs into common LCI databases and families of impact methods. Without such links, newly proposed methods are usually limited in applicability. Therefore, it is recommended to increase efforts towards the integration of already proposed impact categories targeting ecosystem services, which would increase the coverage from an average of 4 to approximately 10 out of 15 ecosystem services categories proposed as optimal.

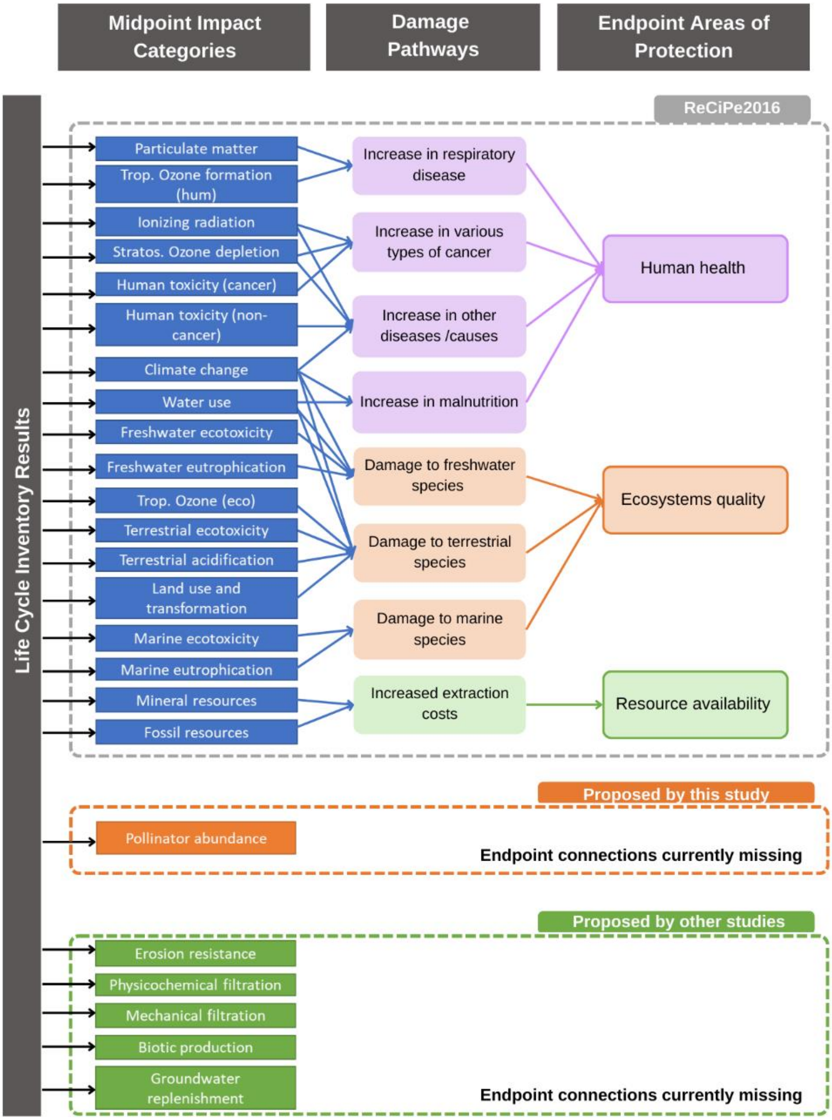

Figure 6.1 *Overview of impact categories from ReCiPe2016 and those proposed to include ecosystem services in LCA.*

6.1.2 Proposing a new impact category: Land use impacts on wild pollinator abundance

One of the ecosystem services identified as missing from LCA studies in Chapter 2, was the service of crop pollination. While one-third of the global food crops rely on pollination, steep insect declines have led to the estimate that crop production might fall by 5% in high-income countries and 8% in low-to-middle income countries in the absence of pollinators (Hallmann et al. 2017; Koh et al. 2016a; Potts et al. 2010). Even if these numbers are not yet considered dramatic in itself, they will increasingly become so in future since it is likely that our dependence on pollinators will grow over time as global diets diversify towards more nutrient-rich food, among these, fruits, vegetables and nuts (Aizen et al. 2019; Garibaldi et al. 2008). Furthermore, several low-income countries rely on the trade of pollinator dependent crops, such as cocoa, coffee, soybeans, palm oil and avocados, where a steep decline of pollinators would only increase their economic vulnerability. Due to their high relevance for ecosystems and human welfare, the development of a new impact category for LCA targeting the explicit assessment of land use impacts on wild insect pollinator communities was tackled in Chapters 3 and 4.

While searching for existent impact assessment models that could be used to characterize pollination impacts in LCA, we found, as anticipated, that the major limitation for a direct application was the lack of specific temporal and geographical data in LCA that was needed by most methods to determine the amount the pollination supply. Generally, information regarding the location of pollination dependent farms, type of crops grown and estimates of pollinator abundance, are needed by most methods to derive an index of pollinator supply and their contribution to crop pollination and crop yield. Such information is not available in LCAs, because LCA studies rely on inventories where the amount of environmental pressure associated with a product system, in this case the amount of land in use recorded and aggregated in terms of m^2 and m^2·year, are usually deprived of explicit spatial and temporal characteristics, such as georeferenced data or times for pesticide application rates.

To overcome these limitations, Chapter 3 focused on the characterization of pollinator abundance, which is a representative measure on the state of pollinator communities, and it has been positively correlated with their capacity to provide crop pollination services (Genung et al. 2017). After establishing collaboration with an expert in the field of pollination, the information available in LCA inventories was used to derive wild pollinator abundance estimates based on expert knowledge, allowing to characterize the influence of different land use practices on pollinating insects. This approach can be replicated for similar ecosystem services (Figure 6.2), where an ecological feature or process that is directly correlated with the capacity to provide the service can be found within the cause-effect chain, increasing its compatibility for midpoint characterization. Consequently, the application of existing impact assessment models to produce characterization factors, or to derive one, will ultimately depend on the data requirements of the model and their availability in LCI databases. Such data gaps, both for the derivation of CFs and to improve LCA inventories, can be tackled in multiple ways, for example by primary data collection, literature reviews or expert elicitation methods, as illustrated in Chapter 4.

Figure 6.2 *Recommendations to approach the assessment of ecosystem services in LCA and examples from this thesis.*

6.1.3 Deriving readily applicable characterization factors and the importance of interdisciplinary research

To move from illustrative to readily applicable CFs, a bigger sample of pollinator abundance estimates was obtained. To do this, an invitation to collaborate was sent to nearly a hundred experts in the fields of pollination and wild pollinators. From those invited, 25 researchers confirmed participation for a Delphi expert elicitation assessment, and an active collaboration was established. Building up on the characterization approach proposed in Chapter 3, generic CFs were derived in Chapter 4, providing values that allow translation into relative pollinator abundance impacts for 24 land use categories. To retrieve the pollinator abundance estimates for each land use category, the Delphi expert elicitation assessment proved to be a useful method allowing to gather not only quantitative data, but also to obtain argumentation on the characteristics of the landscape associated with each estimate, and to highlight important sources of variation, such as biogeographical differences and management practices.

As a result from the extensive argumentation provided by experts during the Delphi assessment, extensive and intensive levels of agricultural practices were directly correlated with the degree of pollinator abundance impacts. The different degrees of abundance associated with the resulting CFs, were consistent with trends found in the literature, where both modelled and sampled data reflect intensive land use as highly correlated with steep decline rates of pollinator abundance (Bennett et al. 2014; Hallmann et al. 2017; Koh et al. 2016b). This decline has been reported to span several orders of magnitude, across multiple geographic locations and taxonomic groups (Bergholz et al. 2022; Ke et al. 2022; Millard et al. 2021). These findings highlight a key challenge for global food production. Achieving high crop yields can present benefits beyond food security and farmer incomes, as it can help reduce the amount of land needed for food production (Garibaldi et al. 2016; Kwapong et al. 2016; Stein et al. 2017). However, high crop yields are currently achieved in most countries by intense management practices involving a considerable amount of fertilizers and pesticides, which in return reduces ecosystem quality and increases dependency on agricultural inputs (Cole et al. 2020; Dhankher and Foyer 2018). The challenge is therefore to find ways in which crop yields can be increased without compromising ecosystem resilience, including pollinator abundances, for instance by a smart mix of both intensive and extensive practices.

Further modelling efforts are still needed to assess the validity and uncertainty of the CFs proposed, which should be thoroughly analyzed for their integration in decision making. A combination of uncertainty and (global) sensitivity analysis are recommended for future research to aid on the determination of highly influential parameters, their effect on land use, pollinator communities, and the potential tradeoffs when accounting for multiple impact categories. While combined methods of uncertainty and global sensitivity analysis are still not a standard practice in LCA studies, there is a growing body of work aimed at their development as a way to improve the interpretation capacity of life cycle impacts and the identification of highly influential parameters (Blanco et al. 2020; Cucurachi et al. 2022; Cucurachi, Borgonovo, and Heijungs 2016; Kim et al. 2022). Moreover, the variability associated with the (subjective) abundance estimates retrieved for each land use category can serve in future research as informative prior distributions which, once coupled with field data, could help improve the robustness of predictive models of pollinator abundance.

Considerations for the aforementioned parameters is needed to design agro-ecosystems that can manage agricultural inputs and limit the damage to insect populations while providing high food security. This potential tradeoff highlights the need for a better understanding of the benefits that can be achieved by restoration and maintenance practices that can help reestablish floral and nesting resources (Albrecht et al. 2020; Kaiser-Bunbury et al. 2017; Lettow et al. 2018). The benefits of, for example, hedgerows and flower rich field margins, are implicitly accounted for in the high abundance estimates retrieved during the Delphi assessment. However, explicit land use processes addressing these practices are not currently included in life cycle inventories, nor are processes containing information regarding managed pollinators. These are important activities that should be considered for incorporation in the inventory and impact assessment of LCA studies to help distinguish key differences between agricultural systems. From our results, the range between typical and high abundance estimates, as well as the CFs that are based on negative abundance values (reflecting a positive influence on abundance), could be used as the basis for future studies looking for a first approximation or illustrative ways on how to reflect these benefits in LCA.

6.1.4 Addressing regionalization and intranational variation in country-specific characterization factors

An important aspect to address when discussing the implementation of ecosystem services in LCA, is the regional variation of impacts, in particular when discussing land related stressors as the ones characterized in **Chapter 4**. Unlike impacts such as climate change, where an emission of 1kg of CO_2-eq on one side of the world will have the same effect as when it would be emitted on the opposite side, other type of impacts such as those related to land use, will tend to considerably differ based on biogeographical characteristics. To portray these differences, multiple studies have aimed for the development of regionalized CFs (Núñez et al. 2013; Saad et al. 2013) and regionalized impact assessment methods such as LC-Impact (Verones et al. 2016). However, the application of regionalized CFs is generally limited by their compatibility with the spatial scales available in commonly used LCI data (Koellner et al. 2013). Unit process data in LCA databases are usually presented as globally generic and/or country-specific values, as exemplified by the largest and most worldwide used database for LCA, ecoinvent. Therefore, considering countries as the highest level of specificity for most background processes, we explored in **Chapter 5** if the representation of key intranational variations could be better represented when producing country-specific CFs for the case study of soil erosion.

As common practice during the characterization of land use impacts, previous studies had produced country-specific CFs for soil erosion based solely on biogeographical parameters and using the Potential Natural Vegetation (PNV) as a reference state (Beck et al. 2011; Koellner et al. 2013; Saad et al. 2013). The PNV refers to the assumed state that the land would spontaneously develop towards to, if the absence of human action continues during a sufficient length of relaxation time (i.e., regeneration time). A few would argue that PNV represents a natural situation that in some cases cannot be assumed as representative: “If we assume for a moment that all human pressure were to be removed, it would take a long time for a potential natural forest to grow; indeed, it would take so long that the climate would probably change again in that time” (Loidi et al. 2010). Therefore, using the concept of PNV as reference state can complicate the interpretation of results and increase discrepancies on the analysis of land use related impacts. Furthermore, using the PNV as reference state does not allow to allocate or differentiate between the impacts that might have occurred a long time ago and the impact incurred on by the activities related to the functional unit, especially in the case of land transformation impacts. Two other alternative reference states are usually proposed in the literature, one refers to the use of a (quasi-)natural land cover present in each biome/ecoregion, and the other to the 'current mix' of land uses (Koellner et al. 2013; Koellner and Scholz 2008). By using the soil erosion rates associated with each LSA as a reference state in **Chapter 5**, the 'current mix' is used and prevailing soil erosion can be accounted for, ultimately reflecting a more realistic estimate on the potential soil erosion impact that is associated with the functional unit assessed. I argue that this is a more useful impact assessment than a comparison in reference to PNV. While the use of PNV as reference state can help maintain consistency during characterization, our results indicate that the risk of underestimating impacts can be substantial when prevailing degradation is not accounted for, especially for vulnerable areas that might be overlooked when only the most predominant biome or ecoregion per country is assumed as representative.

To elaborate further on the LSAs used in **Chapter 5,** these were produced by Václavík et al. (2013) with the use of self-organized maps (SOMs). SOMs refer to an unsupervised neural network that is trained (using unsupervised learning techniques) to reduce data dimensions and to build a discretized representation from the input samples (Kohonen 2013). In this case, the LSAs were derived from a large amount of data covering a wide range of indicators related to land use intensity, socio-economic and environmental factors. This allowed to identify representative patterns and key characteristics that could be used for the characterization of impacts. While the characterization of soil erosion impacts is usually based solely on biogeographical parameters (e.g., slope, average precipitation, etc.), the regions that were particularly vulnerable to further soil degradation were characterized by a high degree of agricultural inputs, low GDP and strong dependence on agricultural production. Thus, accounting for socio-economic factors can aid on the identification of geographical hotspots that might be overlooked when only ecological parameters are considered (Qin et al. 2021).

Given the large number of indicators that could be used for the derivation of archetypes with the use of SOMs, I recommend to explore the development of an archetype classification that could be used as input across several impact categories (Beckmann et al. 2022; Guinée, 1995). This could be derived from a meta-analysis focusing on data requirements across impact categories, to keep consistency and minimize the proliferation of category-specific archetypes. A combination with uncertainty and sensitivity analysis are further recommended to differentiate the varying effects of quantity and model uncertainties, as well as to allow for the identification of parameters that can drive the largest part of uncertainty associated with a model output (Cucurachi et al. 2022).

Parameters of land use intensity are a clear example of relevant data that can be used across several impact categories, such as type of croplands, fertilizer input, irrigation and yield rates. This data could be used in future research to regionalize the characterization factors presented in **Chapter 4** for pollinator abundance, and provide useful input for measures regarding soil quality and ecological resilience. Moreover, parameters such as species richness, which is used for the characterization of biodiversity impacts, and socio-economic factors such as population density and accessibility, are both useful during midpoint and endpoint characterization of human health related impacts.

Along with the aim to improve the assessment of ecosystem services in LCA, it is inevitable that the number of impact categories available will also expand, highlighting the need to focus integrative efforts on the harmonization of data that can lead to results at spatially relevant scales while facilitating decision making. According to the results obtained in **Chapter 5**, world generic CFs can underestimate over ten times the degree of impacts associated with land use types such as mining, landfill, fallow ground, and permanent crops. Based on these findings, I consider the refinement of country-specific CFs a worthy endeavor that can help improve the representativeness of land use impacts and ES assessment in LCA, without compromising the compatibility of the CFs with inventory scales, and allowing for an easier application and interpretation.

6.2 Limitations and outlook

6.2.1 The issue of land use and land transformation

The environmental impacts addressed in Chapters 3-5, were directly related to land stressors. As explained in Chapter 3, typically two type of land use impacts are assessed in LCA studies: 1) occupation impacts, assessed during the land use phase, and 2) transformation impacts, which considers the time required for an ecosystem to recover after land conversion and abandonment; permanent impacts are usually considered by assuming no regeneration possible and assigning the maximum degree of impact possible. While transformation impacts should provide information on the reversibility of an intervention (i.e., how fast an ecosystem recovers after land conversion), we observed two main discrepancies.

The first discrepancy was found while analyzing the inventory flows recorded for agricultural processes in the main LCA database ecoinvent. The elementary flows for land transformation are currently linked to unit processes by two types of entry: "land transformation from land use type *x*" and "land transformation to land type *y*", as two separate flows (Figure 6.2). The net sum of these two separate flows is then multiplied by their corresponding characterization factor to estimate the land conversion impact (Althaus et al. 2007). However, it was noticed that in multiple relevant agricultural unit processes, the same land use class for transformation "from" and "to" was used, with the same value for each flow (e.g., "transformation *from* $1m^2$ of annual crops" and "transformation *to* $1m^2$ of annual crops"), which implies no net transformation impacts. While the decision on how to allocate transformation impacts is complex and can vary depending on assumptions regarding production output times and reference states, the current approach creates difficulties for interpretation of the results, hindering a clear representation of the contribution of land conversion and occupation flows (Scherer et al. 2021).

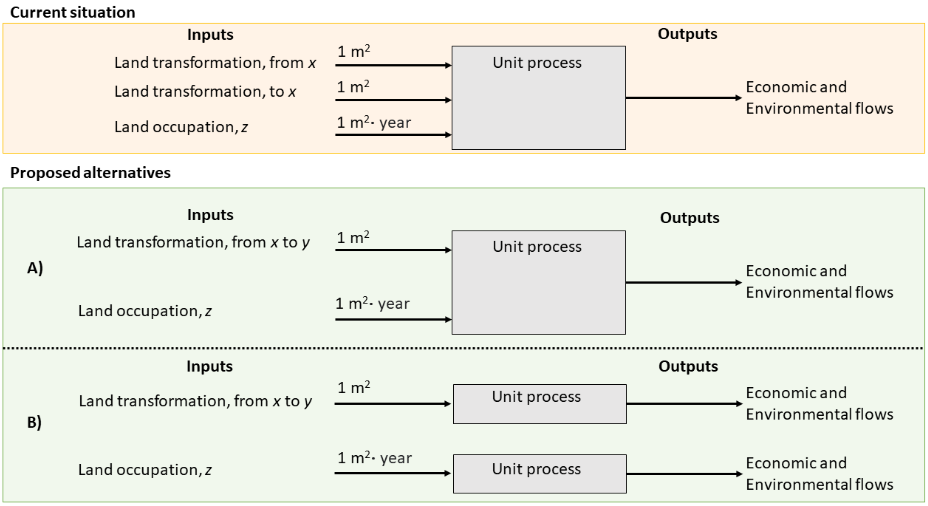

Figure 6.3 *Illustration of land flows connection and proposed alternatives.*

I recommend to address this in future research by exploring the creation of net impact inventories for land transformation flows (Figure 6.3), where a single elementary flow for land transformation (e.g., "land transformation from *x* to *y*') can be used as input for the relevant unit processes and multiplied by their corresponding characterization factor. This new net inventory flow could be included in the same way that both land occupation and transformation flows are used as input in unit processes that incur on land stress (Figure 6.3; alternative proposed A), or by separating the net land transformation flow as input for a land conversion specific unit process (Figure 6.3; alternative proposed B). The latter alternative would allow for additional considerations of land conversion to be modelled independently from land occupation, allowing for an easier analysis of flows contribution.

Furthermore, a detailed analysis proposing net transformation flows could focus on the identification of the most representative land classes to derive characterization factors. For example, the "transformation from *x* to *y*" could be characterized for a set group of the most relevant land use classes, such as forest, grassland, annual and permanent crops, among others. Further specificity could be achieved by targeting the identification of relevant land transformation impacts from land classes within the main categories (e.g., "transformation from annual crop *x* to annual crop *y*"). As discussed in section 6.1.4, special attention will have to be given to the selection of reference states, where the selection between potential natural vegetation or a previous natural state will result in different magnitudes and interpretation of the estimated impacts.

A second discrepancy found was during the characterization of land use impacts, and refers to the fact that multiple methods assume the same effect factor for occupation as for transformation impacts, with the latter multiplied additionally by the regeneration time. This leads to an impact assessment where habitat change is only considered more damaging if the ecosystem recovers slowly, and where the actual impact of land conversion might be misrepresented. Land conversion is one of the primary drivers linked to species decline, and its accurate assessment remains an essential step towards a comprehensive estimation of ecosystem impacts in LCA studies. As displayed by our results in **Chapters 3-4**, we did not produce CFs for land transformation as to not perpetuate practices that seem to undermine efforts towards a better impact characterization. This reinforces the previous recommendation of focusing efforts on an in-depth analysis of how land transformation impacts are currently assessed in LCA, both in terms of inventory data and the development of characterization factors, and propose harmonized ways to improve their assessment.

6.2.2 Societal relevance

The increased acceptance of the LCA framework has resulted in a considerable amount of knowledge produced across several sectors and governmental efforts attempting to quantify environmental pressures. While still acknowledging its limitations, it has led to the recognition of LCA as a representative and valuable method to estimate environmental impacts. A practical example of this is the case of the Netherlands, which is one of the first countries in Europe to legally require a standardized LCA report, in some cases known as Environmental Product Declarations (EPDs), in order to obtain certification for building products and building performance (National Milieu Database 2022; Sobota, Driessenn, and Holländer 2022). For this, companies and governmental organizations are relying on EPDs and LCA results to compare the environmental impacts associated with different material and building design alternatives.

EPDs, and in general LCA results, rely on the availability of impact assessment methods to portray a comprehensive array of environmental impacts, and key ecosystem services remain absent from such comparisons. This can lead to an oversight of impacts and potential benefits associated with sustainable practices. For example, in the case of biomaterials, their increased use is an integral step towards a sustainable built environment (Churkina et al. 2020; Göswein et al. 2021; Vázquez-Núñez et al. 2021). For this, sustainable sourcing of raw materials is indispensable to strive towards regenerative systems and avoid resource depletion. However, common impact assessment methods used in LCA are limited on their ability to reflect key differences between different forest management practices and their influence on the ecosystem services provided by forests, which include but are not limited to, food, fuel and fibers provision, filtration of air pollution and water supplies, control of floods, contribution to soil erosion resistance capacity, biodiversity and genetic resources (as well as cultural ecosystem services related to recreation, education, and cultural enrichment) (Hua et al. 2022; Kiran et al. 2023). Thus, the omission of a comprehensive ecosystem service assessment hinders an accurate representation of the benefits and potential impacts associated with different wood sources and their associated product systems, creating a blind spot during decision-making aimed at a sustainable built environment (Nocentini, Travaglini, and Muys 2022; Tiemann and Ring 2022).

This legal requirement in the building sector clearly illustrates the way in which LCA and other relevant methods are becoming part of governmental efforts aimed at a transition towards more sustainable systems, and highlights the need for a continuous improvement, both in terms of accuracy and coverage, of the impact assessment methods we rely on. To address important shortcomings such as this one, further research is recommended at the interface of LCA and disciplines dedicated at the assessment of environmental impacts, in order to expand and improve the impact assessment and interpretation of LCA results in a meaningful way. For this, extensive collaboration and interdisciplinary work is essential, both to improve the quality of LCI data and for the incorporation of field specific knowledge required in impact assessment models for characterization, as illustrated by this thesis in **Chapter 4**.

6.3 Conclusion

To contribute to the body of knowledge aiming at a better coverage of ecosystem service assessment in LCA studies, this thesis dived into the challenges of incorporating existing ecosystem service methods within the impact assessment phase of the conventional LCA framework. Through this thesis, we present an overview of ecosystem service categories that could represent an optimal coverage for their inclusion in LCA, and provide a clear example on how to overcome the challenges of characterizing key environmental impacts that are otherwise missing or misrepresented in LCA results and that influence the quality and supply of ecosystem services. We demonstrate the approach proposed with the development of readily applicable CFs that will allow future LCA studies to account for land use impacts on pollinator abundance, and provide further evidence on the benefits of interdisciplinary collaboration as a way to strengthen our capacity to estimate anthropogenic impacts, with the use of expert elicitation methods as a valuable tool to fill in key data gaps. Lastly, we recommend to continue efforts towards an overarching archetype classification that can facilitate the inclusion of multiple biogeographical and socio-economic factors for the identification of representative patterns, and provide input across multiple impact categories at relevant spatial scales.

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Abbreviations

AoP	Area of Protection
CF	Characterization Factor
CICES	Common International Classification of Ecosystem Services
EEIOA	Environmental Economic Input Output Analysis
EPD	Environmental Product Declaration
ES	Ecosystem Service
FEGS-CS	Final Ecosystem Goods and Services Classification System
GWP	Global Warming Potential
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LSA	Land System Archetype
MEA	Millenium Ecosystem Assessment
MFA	Material Flow Analysis
NES-CS	National Ecosystem Services Classification System
PNV	Potential Natural Vegetation
ReCiPe	Acronym for RIVM, Radboud University, CML, and Pré Consultants
SETAC	Society of Environmental Toxicology and Chemistry
SOM	Self-Organized Maps
TEEB	The Economics of Ecosystems and Biodiversity
UNEP	The United Nations Environment Program
USES-LCA	Uniform System for the Evaluation of Substances adapted for LCA
WoS	Web of Science

List of symbols

Ar	Area of each archetype within a country
α	Represents an undetermined value of pollinators per m^2 associated with a reference land use type
CF	Characterization factor
K_{use}	Correction factor that reflects the relative degree of soil erosion impact associated with a given land use type
O	Land occupation flows
PA	Pollinator Abundance, expressed in pollinators per m^2
PAO	Pollinator Abundance Occupation, indicator result for land occupation impacts, expressed as relative pollinator abundance decrease.
PO	Probabilities of (land use) Occurrence based on rule of thumb expert estimates expressed in values of 0.1, 0.5, and 1
S_x	Expert estimate of pollinator abundance, expressed on a scale from 0 to 100.
SEO	Soil Erosion Occupation, indicator result for land occupation impacts on soil erosion, expressed in tons of soil eroded.
t_{reg}	Regeneration time

Summary

This thesis explores the incorporation of ecosystem services within the commonly used method of Life Cycle Assessment (LCA). As societies progress in their understanding and acknowledge that the natural environment provides us with vital and irreplaceable resources, so does the urgency to act for an improvement of human activities and avoid irreversible degradation of the environment. This work was motivated by the view that a comprehensive assessment of environmental impacts is indispensable in a transition towards more sustainable societies, which relies on identifying and assessing the multiple impacts caused by human activities. The overarching aim of this work is to bring forward a practical approach to characterize environmental impacts that are associated directly with ecosystem services in a compatible way with LCA.

In Chapter 1 we introduce the concept of ecosystem services, an approach that aims at identifying the multiple benefits that humans derive from the environment and from natural resources. We present the relevance of assessing anthropogenic impacts that affect ecosystem services within methods such as LCA, and provide a general introduction of a standardized framework. We highlight as well the importance of characterization factors, which are used during the impact assessment phase, translating Life Cycle Inventory (LCI) data into potential environmental impacts.

In Chapter 2, we first examined the extent to which ecosystem services have been incorporated within ReCiPe2016, a representative impact assessment method that is commonly used in LCA studies. For this we scrutinized both midpoint and endpoint impact categories, along with their impact characterization models and the ecological aspects considered within each model. We found a handful of impact categories that assess impacts on ecosystem services, and a general lack of guidance in the literature regarding which ecosystem services present compatibilities for future assessment within LCA studies. Addressing this gap, we derived a list of ecosystem service categories based on the Common International Classification of Ecosystem Services (CICES), that could be selected for future assessment in LCA. To achieve an optimal coverage, we recommend future efforts to target the development of new impact categories or the incorporation of ecosystem services in existing ones, which although time consuming, is an endeavor needed

to minimize negative trade-offs when comparing between environmental profiles.

Chapter 3 follows the recommendations derived in the Chapter 2, and targets the incorporation of an ecosystem service identified as missing while developing generalized recommendations for services that present similar characteristics. To do this, Chapter 3 dives into the characterization of land use impacts on pollinator abundance, a measure selected as representative of the state of pollinator communities, with land use identified as the main impact driver of pollinator impacts. Along with the support of an expert in the field of pollination, we successfully illustrate the proposed impact assessment model by deriving an exemplary set of characterization factors that allows to evaluate land use impacts on pollinator abundance in a compatible way to be used in LCA studies.

In Chapter 4, we target key data gaps found in Chapter 3 with an expert elicitation method, and present the first set of readily applicable characterization factors to assess land use impacts on pollinator abundance. To do this, we reached out to experts in the field of pollination which resulted in a panel composed of 25 researchers, spanning 16 nationalities and with a combined experience on more than 40 geographical regions across the globe. A Delphi expert elicitation method consisting of three consecutive rounds of survey was applied, and the statistical convergence of estimates was assessed through a coefficient of variation measure. This successful collaboration exemplifies clearly the way that interdisciplinary research is essential to overcome limitations that can hinder the assessment of key ecosystem services.

In Chapter 5, we explore the use of land system archetypes to characterize soil erosion impacts and assess the representation of intra-national differences in country specific characterization factors. From the characterization factors obtained, covering 263 countries and 8 land use types, the results indicate a high variability when all the archetypes within a country were accounted for. Hence, the impact characterization showed higher variability than when using solely the most predominant archetype within a country. An alternative reference state, the 'current land use mix' was used instead of the Potential Natural Vegetation, which allowed to account for prevailing soil degradation. With information derived from land system archetypes, we were able to identify vulnerable areas based on both biogeographical and socioeconomic aspects. The use of archetypes is recommended as a promising avenue of research to further regionalize the characterization of land use impacts at compatible scales with LCI data.

Chapter 6 builds on the experiences and insights from the previous chapters to propose generalized recommendations to tackle the assessment of ecosystem services in LCA. Furthermore, we address in this chapter some of the challenges encountered during the characterization of land use impacts. We highlight as well the relevance of continuously improving and expanding the coverage of environmental impacts assessed in LCA studies. With the increasing acceptance of the LCA method, the demands for its representativeness to compare the environmental implications of product and service systems also increases and ecosystem services assessment should be one of them.

Altogether, we envision the work of this thesis to contribute to the body of knowledge aimed at a better coverage of environmental impacts, and supports future research by presenting a practical approach to tackle the development of new impact categories that address ecosystem services.

Samenvatting

Dit proefschrift onderzoekt de integratie van ecosysteemdiensten binnen de veelgebruikte methode van Levenscyclusanalyse (LCA). Naarmate samenlevingen vooruitgang boeken in hun begrip en erkenning dat het natuurlijke milieu ons voorziet van vitale en onvervangbare hulpbronnen, groeit ook de urgentie om actie te ondernemen voor verbetering van menselijke activiteiten en het vermijden van onomkeerbare degradatie van het milieu. Dit werk werd gemotiveerd door de opvatting dat een uitgebreide beoordeling van milieueffecten onmisbaar is in een overgang naar meer duurzame samenlevingen. Voor zo'n beoordeling is het identificeren en beoordelen van de meervoudige effecten veroorzaakt door menselijke activiteiten cruciaal. Het overkoepelende doel van dit proefschrift is om een praktische benadering naar voren te brengen om milieueffecten te karakteriseren die rechtstreeks verband houden met ecosysteemdiensten op een manier die implementeerbaar is in LCA.

In Hoofdstuk 1 introduceren we het concept van ecosysteemdiensten, een benadering die tot doel heeft de vele voordelen te identificeren die mensen krijgen uit het milieu en de natuurlijke hulpbronnen. We presenteren de relevantie van het beoordelen van door de mens veroorzaakte effecten die ecosysteemdiensten beïnvloeden binnen methoden zoals LCA, en geven een algemene introductie van de gebruikte concepten in dit proefschrift. We benadrukken ook het belang van de zogenaamde karakteriseringsfactoren, die worden gebruikt tijdens de impactbeoordelingsfase, om Life Cycle Inventory (LCI) gegevens om te zetten naar potentiële milieueffecten.

In Hoofdstuk 2 onderzochten we allereerst in hoeverre ecosysteemdiensten al zijn geïntegreerd in ReCiPe2016, een representatieve impactbeoordelingsmethode die veel wordt gebruikt in LCA-studies. Hiervoor hebben we zowel middelpunt- als eindpunt-impactcategorieën kritisch bekeken, samen met hun impactkarakteriseringmodellen en de ecologische aspecten die binnen elk model worden beschouwd. We vonden slechts een handvol impactcategorieën die effecten op ecosysteemdiensten beoordelen, en een algemeen gebrek aan richtlijnen in de literatuur over welke ecosysteemdiensten compatibiliteit bieden voor toekomstige beoordelingen binnen LCA-studies. Om deze lacune aan te pakken, hebben we een lijst van ecosysteemdienstcategorieën afgeleid op basis van de Common International Classification of Ecosystem Services (CICES), die in de toekomst kan worden

aangepakt voor beoordelingen in LCA. Om een optimale dekking te bereiken, raden we toekomstige inspanningen aan om nieuwe impactcategorieën te ontwikkelen of om ecosysteemdiensten op te nemen in bestaande categorieën, wat hoewel het tijdrovend is, een inspanning is die nodig is om negatieve effecten op andere ecosysteemdiensten te minimaliseren bij het vergelijken van milieuaspecten.

Hoofdstuk 3 volgt de aanbevelingen uit Hoofdstuk 2 en richt zich op de integratie van een ecosysteemdienst die ontbreekt, terwijl algemene aanbevelingen worden gedaan voor diensten met vergelijkbare kenmerken. Om dit te doen, duikt Hoofdstuk 3 in de karakterisering van de impact van landgebruik op de aanwezigheid van bestuivers. De aanwezigheid van bestuivers wordt representatief geacht voor de toestand van bestuiversgemeenschappen in het algemeen en landgebruik wordt gezien als de belangrijkste veroorzaker van effecten op bestuiving. Met de hulp van een expert op het gebied van bestuiving illustreren we succesvol het voorgestelde impactbeoordelingsmodel door een reeks karakteriseringsfactoren af te leiden die landgebruikseffecten op de aanwezigheid aan bestuivers op een passende manier weergeven en in LCA-studies kunnen worden gebruikt.

In Hoofdstuk 4 richten we ons op de belangrijkste gaten in de beschikbare gegevens zoals die zijn gevonden in Hoofdstuk 3 met behulp van een expert-onthullinggsmethode, en presenteren we een eerste set direct toepasbare karakteriseringsfactoren om de impact van landgebruik op de aanwezigheid van bestuivers te beoordelen. Hiervoor hebben we experts op het gebied van bestuiving benaderd, wat resulteerde in een panel bestaande uit 25 onderzoekers, afkomstig uit 16 verschillende landen en met een gecombineerde ervaring in meer dan 40 geografische regio's over de hele wereld. Een Delphi-expert-onthullingsmethode, bestaande uit drie opeenvolgende rondes van enquêtes, werd toegepast, en de statistische convergentie van schattingen werd beoordeeld aan de hand van een maat voor variatie in de antwoorden. Deze succesvolle samenwerking illustreert duidelijk hoe interdisciplinair onderzoek essentieel is om beperkingen te overwinnen die de beoordeling van belangrijke ecosysteemdiensten kunnen belemmeren.

In Hoofdstuk 5 verkennen we het gebruik van landgebruik-archetypen om de impact van bodemerosie te karakteriseren en de representatie van intra-nationale verschillen in karakteriseringsfactoren te beoordelen. Uit de verkregen karakteriseringsfactoren, die 263 landen en 8 landgebruikstypen omvatten, blijkt dat er een grote variabiliteit is wanneer alle archetypen binnen een land worden meegenomen tijdens de impactkarakterisering. Die variatie is veel lager wanneer alleen het meest overheersende archetype binnen een land wordt gebruikt. Er werd gebruik gemaakt van een alternatieve referentiestaat, het 'de mix aan huidige landgebruik', in plaats van de Potentiële Natuurlijke Vegetatie, waardoor rekening werd gehouden met de heersende bodemdegradatie. Met informatie afgeleid van landgebruik-archetypen waren we in staat kwetsbare gebieden te identificeren op basis van zowel biogeografische als sociaaleconomische aspecten. Het gebruik van archetypen wordt aanbevolen als een veelbelovende onderzoeksrichting om de karakterisering van landgebruikseffecten verder te regionaliseren op schalen die overeen komen met LCI-gegevens.

Hoofdstuk 6 bouwt voort op de ervaringen en inzichten uit eerdere hoofdstukken om algemene aanbevelingen te doen voor de beoordeling van ecosysteemdiensten in LCA. Bovendien gaan we in dit hoofdstuk in op enkele van de uitdagingen die zijn ondervonden tijdens de karakterisering van landgebruikseffecten. We benadrukken ook het belang van voortdurende verbetering en uitbreiding van de dekking van milieueffecten die worden beoordeeld in LCA-studies, vanwege de toenemende acceptatie van de LCA-methode als een representatieve manier om de milieueffecten van product- en dienstsystemen te vergelijken.

Al met al voorzien we dat het werk van dit proefschrift zal bijdragen aan de kennis op het gebied van een betere dekking van milieueffecten en ondersteuning zal bieden voor toekomstig onderzoek door een praktische benadering te presenteren voor de ontwikkeling van nieuwe impactcategorieën die ecosysteemdiensten aanpakken.

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Curriculum Vitae

Elizabeth Migoni Alejandre was born in 1991 and grew up in the coastal city of Ensenada, Baja California, Mexico. In 2007 she moved for a year to the city of Arlon, in the south of Belgium, as part of the 'World Exchange Program', completing a year of secondary education at the Athénée Royal d'Arlon. In 2014, she obtained her bachelor's degree in Biology at the Autonomous University of Baja California. During her first years of bachelors, she specialized on molecular biology at the department of Biotechnology & Immunology, where she worked as a research intern on the development of genetically modified microalgae for the production of vaccines and biofuels, and later on, on the development of a fast H1N1 Flue test with llama antibodies. Her studies were complemented by extensive volunteer work in multidisciplinary fields, where after a summer onboard of a Physical Oceanographic research cruise led by CICESE research center, her interests radically shifted towards environmental studies.

In 2014, she obtained a National Science and Engineering Scholarship awarded by the Mexican government for graduate studies abroad and moved in 2015 to The Netherlands, to pursue a M.Sc. degree in Industrial Ecology at the Institute of Environmental Sciences (CML) of Leiden University. In her master thesis she explored the comparison of alternative baselines for the characterization of land use impacts on ecosystem services for Life Cycle Assessment (LCA). Once graduated, she started her PhD studies on further exploring the potential of assessing ecosystem service impacts in LCA studies, focusing on the challenges of impact assessment characterization and spatial differentiation. Throughout the period 2017-2022, Elizabeth also worked part-time as environmental consultant for companies such as GoodFuels and The Ocean Cleanup, and as project lead at the Urban Energy Institute at the Delft University of Technology (TU Delft). Aiming at a never-ending challenge of exploring new fields and working at the interface of multiple disciplines, Elizabeth has worked since 2022 as researcher at TU Delft, assessing the environmental implications of biomaterials and their application in the built environment.

Between a pile of fiction novels and acrylic paint, Elizabeth enjoys sketching characters living in surreal planetary landscapes, listening to music, and constantly seeking for the hidden delights of everyday life.