DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

PHD PROGRAMME IN ENVIRONMENTAL ENGINEERING

DOCTORAL THESIS

ENVIRONMENTAL IMPACT ACCOUNTING OF ORGANIC AGRICULTURAL PRODUCTION SYSTEMS: ADVANCING INVENTORY AND BIODIVERSITY MODELLING APPROACHES IN LIFE CYCLE ASSESSMENT

ERICA YVONNE MONTEMAYOR

INSTITUT DE RECERCA I TECHNOLOGIA AGROALIMENTARIES (IRTA)

INSTITUTE OF AGRI-FOOD RESEARCH AND TECHNOLOGY

DIRECTORS:

DR. ASSUMPCIÓ ANTÓN

DR. AUGUST BONMATÍ

TUTOR:

DR. SANTIAGO GASSÓ DOMINGO

SEPTEMBER 2022

ACKNOWLEDGEMENTS

First and foremost, to the people who gave me this great opportunity, my supervisors Dr. Assumpció Antón and Dr. August Bonmatí, and my tutor at UPC, Dr. Santiago Gassó. I remember my first interview with Dr. Antón and Dr. Bonmatí for a job at IRTA as an LCA technician. Even though my Spanish was quite poor at the time, they still saw something in me and trusted me with the job. I was ecstatic when the opportunity came up to do a doctorate with them in a crossover between two fields I am deeply passionate about, environmental life cycle assessment and organic agriculture. I will be forever grateful to them for the opportunity and helping me achieve something I always dreamed of. Especially to Assumpció who was the guiding light in my work, always supportive, encouraging and pushing me to be my best self, I could not ask for a better supervisor and friend. You inspire me with your passion for your work, and your empathy and supportive nature for all the people around you. You are the definition of a great leader.

To all my friends at IRTA, present and gone, Lluis, Edu, Josep, Miriam Guivernau, Laura Burgos, Laura Tey, Ana Otero, Marlene, Mar, thank you for your friendship, laughs, patience with my Spanish, lunches in the comedor and fun activities with team building. You made my time at IRTA so enjoyable!

Thanks especially to the LCA team that supported me throughout my journey, Marta, Ariadna, Montse, Ralph, Miquel and especially my UN friends (inside joke) Nancy and Edilene. I look forward to coming to the office because of you! I have never felt alone in my work knowing I had your friendship and support. I am so grateful to all of you for making this journey so much fun! And I look forward to so much more! I am so lucky to have worked with such a loving and talented group of people.

To my husband, Jaume, without your love and support much of this would not have been possible. You comfort, inspire and encourage me through the toughest times, and celebrate and cheer me on in all my achievements. Thank you for being my rock, my half orange. We did this together!

And finally, to my loving family, Mom, Dad, Elisa, Rachelle, Roy (all the kids), James, Anjee, Melissa and Hazel. Thank you for believing in me, encouraging me to follow my dreams and trusting in my choices to move abroad, though it could be hard at times. I am so happy and lucky to have such a supportive family that I can lean and depend on in the good times and the bad. You are the people who make me the happy, smiley person I am! And especially to my late father, who looked forward to this day, this is for you.

TABLE OF CONTENTS

I. LIST OF TABLES

APPENDIX TABLES:

II. LIST OF FIGURES

APPENDIX FIGURES

III. LIST OF ACRONYMS

ADP	Air acidification potential
AG	AGRIBALYSE database
BDP	Biodiversity Damage Potential
CAP	Common Agricultural Policy
c-SAR	Countryside species-area-relationship
CCP	Climate Change Potential
CeBER	Centre for Bioprocess Engineering Research
CF	Characterization Factor
CONV	Conventional agricultural practices
EC	European Commission
EI	Ecoinvent database
ES1	Spanish case study 1
ES2	Spanish case study 2
EU	Europe
FAO	Food and Agriculture Association of the United Nations
FEP	Freshwater Eutrophication Potential
FEx	Freshwater Ecotoxicity Potential
FU	Functional Unit
GEP	Global extinction probability
GLAM	Global Life Cycle Impact Assessment Method
IUCN	International Union for Conservation of Nature
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment

LEAP	Livestock Environmental Assessment and Performance of the FAO
LU	Land Use
LUP	Land use potential
LW	Live Weight
MEP	Marine Eutrophication Potential
NO1	Norwegian case study 1
OA	Organic Agriculture
ODP	Ozone depletion Potential
ORG	Organic agricultural practices
PDF	Potential disappeared Fraction
PhACs	Pharmaceutical Active Compounds
PPP	Plant Protection Products
PSL	Potential Species Loss
REP	Resource energy use
RMP	Resource mineral use
SAR	Species-area-relationship
SETAC	Society of Environmental Toxicology and Chemistry
SHR	Species-habitat-relationship
TEP	Terrestrial Eutrophication potential
UNEP	United Nations Environment Programme

IV. PREFACE

The work presented in this thesis is part of the Organic-PLUS Horizon 2020 project, “Pathways to phase-out contentious inputs from organic agriculture in Europe” (Grant agreement 774340) and thus funded thanks to the European Commission’s Horizon 2020 Programme. The research work was carried out at the Institute of Agri-food Research and Technology of Catalonia (IRTA) and within the Environmental Engineering PhD Programme at the Department of Civil and Environmental Engineering at the Polytechnic University of Catalonia (UPC). The main objective of the thesis was to analyze and improve environmental impact accounting of organic agricultural systems using Life Cycle Assessment (LCA) methodology.

Thesis supervision was carried out by Dr. Assumpció Antón (Senior Researcher at IRTA) and Dr. August Bonmatí (Senior Researcher at IRTA), and tutored by Prof. Dr. Santiago Gassó (UPC).

This PhD thesis is mainly formed through the compilation of three scientific papers. One of them (Chapter 2) was already published in a Q1 peer-reviewed international scientific journal. The other two (Chapters 3 and 4) have already been sent for publication in Q1 journals and are currently under review. The list of the articles are as follows:

I. **Published article:**

- **Montemayor, E.**, Andrade, E.P., Bonmatí, A. et al. Critical analysis of life cycle inventory datasets for organic crop production systems. Int J Life Cycle Assess 27, 543–563 (2022). https://doi.org/10.1007/s11367-022-02044-x

II. **Submitted articles:**

- **Montemayor, E.**, Bonmatí, A., Andón, M., Antón, A. Analysis of top-down and bottom-up approaches for modelling biodiversity loss in agricultural systems using life cycle assessment: a case study of livestock production in Europe. Submitted to the journal Environmental Science and Technology. Under review.

- **Montemayor, E.**, Knudsen, M.T., Bonmatí, A., Antón, A. Life cycle assessment characterization factors for land use impacts on biodiversity in organic and conventional farmland in the European Mediterranean biome. Submitted to the Journal of Cleaner Production. Under review.

Furthermore, based on the research developed, the following contributions to international congresses were performed as the main author:

1. **Montemayor, E**.; Knudsen, M.T.; Bonmatí, A.; Ruiz-Colmenero, M.; Antón, A. 2022. Land use-specific characterization factors to assess biodiversity of conventional and organic woody

perennial and annual arable crops in the European Mediterranean Biome. 13th International Conference on Life Cycle Assessment of Food 2022 (LCA Foods 2022). Lima, Peru.
Type of presentation: Oral

2. **Montemayor, E**.; Knudsen, M.T.; Bonmatí, A.; Antón, A. 2022. Life cycle assessment characterization factors for land use impacts on biodiversity in organic and conventional farmland in the European Mediterranean biome. 32nd SETAC (Society of Environmental Toxicology and Chemistry) Europe Annual Meeting.
Type of presentation: Oral (virtual)

3. **Montemayor, E**.; Bonmatí, A.; Antón, A. 2021. Modelling the environmental impacts of organic agriculture: critical aspects of the goal, scope and life cycle inventory in LCA. 31st SETAC Europe Annual Meeting.
Type of presentation: Poster (virtual)

4. **Montemayor, E**.; Pereira, E.; Bonmatí, A.; Antón, A. 2020. LCA tools: appraising their background to evaluate alternatives to contentious inputs in organic agriculture. International Conference on Life Cycle Assessment of Food (LCA Food 2020).
Type of presentation: Poster (virtual)

5. **Montemayor, E**.; Martí, S.; Antón, A. 2019. Testing land use biodiversity indicators in organic and conventional beef production systems. 29th SETAC Europe Annual Meeting. Helsinki, Finland.
Type of presentation: Spotlight poster

Other publications and congresses outside of this thesis include:

1. Andrade, E.P., Bonmati, A., Esteller, L.J., **Montemayor, E.,** Vallejo, A.A., 2021. Performance and environmental accounting of nutrient cycling models to estimate nitrogen emissions in agriculture and their sensitivity in life cycle assessment. Int. J. Life Cycle Assess. 26, 371–387. https://doi.org/10.1007/s11367-021-01867-4

2. **Montemayor, E.**, Bonmatí, A., Torrellas, M., Camps, F., Ortiz, C., Domingo, F., Riau, V., Antón, A., 2019. Environmental accounting of closed-loop maize production scenarios: Manure as fertilizer and inclusion of catch crops. Resour. Conserv. Recycl. 146. https://doi.org/10.1016/j.resconrec.2019.03.013
3. **Montemayor, E**.; Antón, A.; Bonmatí, A. 2020. Improving manure management towards a more carbon & nutrient efficient agriculture. International Conference on Life Cycle Assessment of Food. **Type of presentation: Poster (virtual)**

4. **Montemayor, E.**, Peña, N., Bonmatí, A., Camps, F., Ortiz, C., Domingo, F., Riau, V., Antón, A. 2019. Farms for the future as part of the circular economy package: the need to account for better

environmental performance. VIII International Conference on Life Cycle Assessment in Latin America (CILCA). Cartago, Costa Rica. **Type of presentation: Oral**

5. **Montemayor, E**., Bonmatí, A., Camps, F., Ortiz, C., Domingo, F., Pereira, E., Antón, A. 2019. Environmental accounting of manure fertilization: case study of circular maize and catch crop feed scenarios. ManuResource International Conference. Hasselt, Belgium. **Type of presentation: Oral**

V. ABSTRACT

Agriculture not only contributes to more than a quarter of all global greenhouse gas emissions but is also the number one anthropogenic source of nitrogen emissions and a danger to nearly half of threatened terrestrial species. Organic agriculture has been proposed as a possible solution to reduce environmental impacts due to agricultural practices, since it prioritizes environmental protection and animal welfare considerations, prioritizing preventative techniques in order to preserve ecosystems and resources. In Europe, it has been legally defined as method of farming since 1991. Organic agriculture has been found to be similar or superior to conventional agriculture in terms of environmental performance, using the internationally standardized methodology called Life Cycle Assessment (LCA). It follows a life cycle perspective and is widely used due to its holistic vision, including both the whole production chain concept and multi-criteria environmental indicators, as well as its quantitative, scientific approach to estimating environmental impacts. However, LCA does not always fully reflect organic production systems accurately, leaving out important aspects such as ecosystem services like biodiversity. Thus, research was carried out to explore how LCA can be improved in order to accurately and comprehensively account for the environmental impact of organic agricultural systems. Firstly, life cycle inventory (LCI) datasets from current and recommended LCA databases were critically analyzed to see if they accurately reflect organic practices. Secondly, current and recommended life cycle impact assessment (LCIA) biodiversity loss models were also analyzed and tested using a livestock case study for their scope and context suitability. Finally, using the results from that analysis, a model was chosen to develop new LCIA characterization factors for potential disappeared fraction of plants due to organic crop land use compared to conventional crops in the European Mediterranean biome.

Through the critical analysis of organic crop LCI datasets, it was found that unrepresentative plant protection product (PPP) production and organic fertilizer treatment inventories were the main limitations in background processes, due to either the lack of available usage statistics, exclusion from the study or use of unrepresentative proxies. Many organic crop LCIs used synthetic pesticide or mineral fertilizer proxies, which may indirectly contain OA prohibited chemicals. These critical aspects can be transferred to respective LCAs that use this data, potentially yielding unrepresentative results. To improve accuracy, new production LCIs were created for three PPPs, as well as recommendations for fertilizer treatment LCIs and more precise emission models for PPPs and fertilizers.

In regards to biodiversity loss indicators, the currently recommended top-down indicator was found to be inadequate for site-specific agricultural practices like organic farming, due to the inability of the characterization factors to significantly differentiate between light and minimal management intensity and pasture and cropland in our case study. Whereas the bottom-up model was found to be more suitable due to its site-specificity. Recommendations were given on how to improve the studied biodiversity LCIA models. The new LCIA characterization factors estimating PDF of plants, demonstrated that the potential plant species loss on perennial woody organic cropland could not be differentiated from their conventional counterparts if the conventional system was quite extensive, but were significantly different in intensive systems. Further sub-classes of conventional perennial woody crop systems should be made. Significant differences were found between CFs for organic and conventional arable crop systems.

This thesis provides for the first time, novel critical analysis of organic crop LCIs, new LCIs for PPP manufacturing, and testing and guidance on the use of different top-down and bottom-up biodiversity LCIA models. Additionally, this thesis presents for the first time new LCIA characterization factors for potential disappeared fraction of plants on both organic and conventional cropland. Hence, helping to improve the modelling of LCA application to organic production systems. Furthermore, future research ideas are proposed at the end of this thesis, such as developing toxicity characterization factors for PPP, critical analysis of organic livestock LCIs, and how to include other important aspects of organic livestock systems like landscape aesthetics and animal welfare.

VI. RESUM

L'agricultura no només contribueix a més d'una quarta part de totes les emissions mundials de gasos d'efecte hivernacle, sinó que també és la font antropogènica número u d'emissions de nitrogen i un perill per a gairebé la meitat de les espècies terrestres amenaçades. L'agricultura ecològica s'ha proposat com una possible solució per reduir els impactes ambientals deguts a les pràctiques agrícoles, ja que prioritza les consideracions de protecció ambiental i benestar animal, prioritzant les tècniques preventives per tal de preservar ecosistemes i recursos. A Europa es defineix legalment com a mètode de cultiu des de l'any 1991. S'ha trobat que l'agricultura ecològica és similar o superior a l'agricultura convencional pel que fa al rendiment ambiental, utilitzant la metodologia estandarditzada internacionalment anomenada Avaluació del Cicle de Vida (ACV, o LCA en les seves sigles en anglès). LCA segueix una perspectiva de cicle de vida i s'utilitza àmpliament per la seva visió holística, que inclou tant el concepte de la cadena de producció com els indicadors ambientals multicriteris, així com el seu enfocament científic i quantitatiu per estimar els impactes ambientals. Tanmateix, la LCA no sempre reflecteix completament els sistemes de producció orgànica amb precisió, deixant de banda aspectes importants com els serveis ecosistèmics com la biodiversitat. Així, es va dur a terme una investigació per explorar com es pot millorar la LCA per tal de tenir en compte de manera precisa i exhaustiva l'impacte ambiental dels sistemes agrícoles orgànics. En primer lloc, es van analitzar críticament els conjunts de dades d'inventari de cicle de vida (ICV o LCI en les seves sigles en anglès) de les bases de dades de LCA actuals i recomanades per veure si reflecteixen amb precisió les pràctiques orgàniques. En segon lloc, també es van analitzar i provar els models de pèrdua de biodiversitat actuals i recomanats de l'avaluació d'impacte del cicle de vida (AICV o LCIA en les seves sigles en anglès) mitjançant un estudi de cas de bestiar pel seu abast i adequació al context. Finalment, utilitzant els resultats d'aquesta anàlisi, es va escollir un model per desenvolupar nous factors de caracterització LCIA per a la possible fracció de plantes desapareguda a causa de l'ús del sòl de cultius orgànics en comparació amb els cultius convencionals al bioma mediterrani europeu.

Mitjançant l'anàlisi crítica dels conjunts de dades d'LCI de cultius orgànics, es va trobar que la producció no representativa de productes fitosanitaris (PPP) i els inventaris de tractament de fertilitzants orgànics eren les principals limitacions en els processos de fons, a causa de la manca d'estadístiques d'ús disponibles, l'exclusió de l'estudi o ús de proxies no representatius. Molts LCI de cultius orgànics utilitzaven pesticides sintètics o fertilitzants minerals substitutius, que poden contenir indirectament productes químics prohibits per OA. Aquests aspectes crítics es poden transferir a les respectives LCA que utilitzen aquestes dades, la qual cosa pot produir resultats poc representatius. Per millorar la precisió, es

van crear nous LCI de producció per a tres PPP, així com recomanacions per als LCI de tractament de fertilitzants i models d'emissió més precisos per a PPP i fertilitzants.

Pel que fa als indicadors de pèrdua de biodiversitat, l'indicador top-down recomanat actualment és inadequat per a pràctiques agrícoles específiques del lloc com l'agricultura ecològica, a causa de la incapacitat dels factors de caracterització per diferenciar significativament entre la intensitat de gestió lleugera i mínima i les pastures i les terres de cultiu en el nostre cas pràctic. Mentre que el model bottom-up es va trobar més adequat a causa de la seva especificitat del lloc. Es van donar recomanacions sobre com millorar els models LCIA de biodiversitat estudiats. Els nous factors de caracterització LCIA que estimaven el PDF de les plantes, van demostrar que la pèrdua potencial d'espècies vegetals a les terres de cultiu orgàniques llenyoses perennes no es podria diferenciar de les seves contraparts convencionals si el sistema convencional era força extensiu, però eren significativament diferents en sistemes intensius. S'han de fer més subclasses de sistemes de cultius llenyosos perennes convencionals. Es van trobar diferències significatives entre els CF per als sistemes de cultius orgànics i convencionals.

Aquesta tesi ofereix per primera vegada una nova anàlisi crítica dels LCI de cultius orgànics, nous LCI per a la fabricació de PPP i proves i orientacions sobre l'ús de diferents models LCIA de biodiversitat top-down i bottom-up. A més, aquesta tesi presenta per primera vegada nous factors de caracterització LCIA per a possibles fraccions desaparegudes de plantes tant en terres de cultiu orgàniques com convencionals. Per tant, ajuda a millorar la modelització de l'aplicació de l'LCA als sistemes de producció ecològica. A més, al final d'aquesta tesi es proposen idees de recerca futures, com ara el desenvolupament de factors de caracterització de toxicitat per a PPP, l'anàlisi crítica dels LCI de bestiar orgànic i com incloure altres aspectes importants dels sistemes de ramaderia orgànica com l'estètica del paisatge i el benestar animal.

VII. RESUMEN

La agricultura no solo contribuye a más de una cuarta parte de todas las emisiones globales de gases de efecto invernadero, sino que también es la principal fuente antropogénica de emisiones de nitrógeno y un peligro para casi la mitad de las especies terrestres amenazadas. La agricultura orgánica se ha propuesto como una posible solución para reducir los impactos ambientales debido a las prácticas agrícolas, ya que prioriza la protección ambiental y el bienestar animal, priorizando las técnicas preventivas para preservar los ecosistemas y los recursos. En Europa, se ha definido legalmente como un método de agricultura desde 1991. Se ha encontrado que la agricultura orgánica es similar o superior a la agricultura convencional en términos de desempeño ambiental, utilizando la metodología estandarizada internacionalmente llamada Evaluación del Ciclo de Vida (LCA). LCA sigue una perspectiva de ciclo de vida y es ampliamente utilizado debido a su visión holística, que incluye tanto el concepto de toda la cadena de producción como los indicadores ambientales multicriterio, así como su enfoque cuantitativo y científico para estimar los impactos ambientales. Sin embargo, LCA no siempre refleja completamente los sistemas de producción orgánica con precisión, dejando de lado aspectos importantes como los servicios ecosistémicos o la biodiversidad. Por lo tanto, se llevó a cabo una investigación para explorar cómo se puede mejorar el LCA para considerar de manera precisa y completa el impacto ambiental de los sistemas agrícolas orgánicos. En primer lugar, se analizaron críticamente los conjuntos de datos del inventario del ciclo de vida (LCI) de las bases de datos LCA actuales y recomendadas para ver si reflejan con precisión las prácticas orgánicas. En segundo lugar, también se analizaron y probaron los modelos actuales y recomendados de evaluación del impacto del ciclo de vida (LCIA) utilizando un estudio de caso de ganado para determinar su alcance y adecuación al contexto. Finalmente, utilizando los resultados de ese análisis, se eligió un modelo para desarrollar nuevos factores de caracterización LCIA para la posible fracción desaparecida de plantas debido al uso de la tierra para cultivos orgánicos en comparación con los cultivos convencionales en el bioma mediterráneo europeo.

A través del análisis crítico de los conjuntos de datos de LCI de cultivos orgánicos, se encontró que la producción no representativa de productos fitosanitarios (PPP) y los inventarios de tratamiento de fertilizantes orgánicos eran las principales limitaciones en los procesos de fondo, debido a la falta de estadísticas de uso disponibles, la exclusión del estudio o uso de apoderados no representativos. Muchos LCI de cultivos orgánicos utilizaron sustitutos de pesticidas sintéticos o fertilizantes minerales, que indirectamente pueden contener sustancias químicas prohibidas por OA. Estos aspectos críticos se pueden transferir a las respectivas LCA que utilizan estos datos, lo que podría generar resultados no

representativos. Para mejorar la precisión, se crearon nuevos LCI de producción para tres PPP, así como recomendaciones para LCI de tratamiento de fertilizantes y modelos de emisión más precisos para PPP y fertilizantes.

Con respecto a los indicadores de pérdida de biodiversidad, se encontró que el indicador top-down actualmente recomendado era inadecuado para prácticas agrícolas específicas del sitio, como la agricultura orgánica, debido a la incapacidad de los factores de caracterización para diferenciar significativamente entre intensidad de manejo ligera y mínima y pastizales y tierras de cultivo en nuestro caso de estudio. Sin embargo, se encontró que el modelo bottom-up era más adecuado debido a su especificidad de sitio. Se dieron recomendaciones sobre cómo mejorar los modelos LCIA de biodiversidad estudiados. Los nuevos factores de caracterización de LCIA que estiman la PDF de las plantas demostraron que la pérdida potencial de especies de plantas en tierras de cultivo orgánicas leñosas perennes no podía diferenciarse de sus contrapartes convencionales si el sistema convencional era bastante extensivo, pero eran significativamente diferentes en los sistemas intensivos. Deberían crearse otras subclases de sistemas de cultivos leñosos perennes convencionales. Se encontraron diferencias significativas entre los CF para sistemas de cultivos herbáceos orgánicos y convencionales.

Esta tesis proporciona, por primera vez, un análisis crítico novedoso de LCI de cultivos orgánicos, nuevos LCI para la fabricación de PPP y pruebas y orientación sobre el uso de diferentes modelos LCIA de biodiversidad de top-down y bottom-up. Además, esta tesis presenta por primera vez nuevos factores de caracterización LCIA para la posible fracción de plantas desaparecidas en cultivos orgánicos y convencionales. Por lo tanto, ayuda a mejorar el modelado de la aplicación de LCA a los sistemas de producción orgánica. Además, al final de esta tesis se proponen ideas de investigación futuras, como el desarrollo de factores de caracterización de toxicidad para PPP, el análisis crítico de LCI de ganado orgánico y cómo incluir otros aspectos importantes de los sistemas de ganado orgánico como la estética del paisaje y el bienestar animal.

VIII. STRUCTURE OF THE THESIS

The present PhD thesis was structured in six chapters and four annexes, as follows:

Chapter 1. Introduction

In this chapter, the necessary background information is provided, including an explanation of organic agriculture in Europe and life cycle assessment methodology. An exploration of the state-of-the-art in LCA in organic agriculture and its effects on biodiversity was provided.

Chapter 2. Critical analysis of organic crop life cycle inventories

An in-depth analysis of the state-of-the-art life cycle inventories in LCA is made, including the effect of critical gaps on LCA results, and specific ways to improve LCI of organic crops.

Chapter 3. Analysis of top-down and bottom-up LCA approaches for modelling biodiversity loss in agricultural systems

Top-down and bottom-up approaches within LCA for modelling biodiversity were critically analyzed. Using a livestock case study in Europe, gaps were detected and suggestions for use and improvements were given.

Chapter 4. Development of life cycle assessment characterization factors for agricultural land use impacts on biodiversity in the European Mediterranean biome

Using the analysis from Chapter 3, one LCIA method was chosen to develop life cycle characterization factors for land use impacts on biodiversity, specifically for organic and conventional farmland in the European Mediterranean biome, including perennial Mediterranean crops like olives and vineyards.

Chapter 5. Conclusions

This chapter presents the main conclusions obtained in this thesis. Suggestions for future research related to the application of LCA to organic agricultural systems and LCIA biodiversity indicators were provided.

Chapter 6. Bibliographic references

Contains a list of all the bibliographical references cited throughout the thesis document.

Annex A

Extra data and information pertaining to Chapter 1: Introduction.

Annex B

Extra data and information pertaining to Chapter 2: Critical analysis of organic crop life cycle inventories

Annex C

Extra data and information pertaining to Chapter 3: Analysis of top-down and bottom-up LCA approaches for modelling biodiversity loss in agricultural systems

Annex D

Extra data and information pertaining to Chapter 4: Development of life cycle assessment characterization factors for agricultural land use impacts on biodiversity in the European Mediterranean biome

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

1.1.1 ORGANIC AGRICULTURE

Agriculture not only contributes to more than a quarter of all global greenhouse gas emissions (Springmann et al., 2016) but is also the number one anthropogenic source of nitrogen emissions (Ward et al., 2018) and a danger to an estimated 53% of threatened terrestrial species (Tanentzap et al., 2015). Although the green revolution helped feed a growing population, it has also transformed the environment completely. For example, nearly 50% of the land area in Europe is used for crop or pastoral farming, of which 70% is used for livestock and feed (European Commission, 2016). Thus, what can be done to ensure that agricultural land is properly managed to minimize environmental impacts?

Organic agriculture (OA) is often seen as one possible solution to improve agricultural practices. Organic agriculture places emphasis on the use of more natural products and environmentally friendly techniques, preserving ecosystems, conserving resources, and excluding all techniques that can potentially damage the quality of the final product. It avoids or largely minimizes the use of synthetic chemical inputs such as mineral fertilizers, pesticides and medical products like antibiotics used in a preventative manner. In many countries and regions, organic practices are highly regulated, for example, the European Commission has strict regulations on what constitutes organically certified products. Food products are considered certified organic at the EU level if it complies with Council Regulation (EEC) No 2092/91 and its amendments (European Commission, 2008a), which have set up a comprehensive framework for organic farming of crops and livestock and for the labelling, processing and marketing of organic products, whilst also governing imports of organic products into the EU. For example, Table 1 shows the types of fertilizers that are allowed.

Table 1. Fertilizers and soil conditioners permitted in organic agriculture in Europe (EC, 2008).

Fertilizers and soil conditioners	Description
Farmyard manure	Product comprising a mixture of animal excrements and vegetable matter (animal bedding). Factory farming origin forbidden
Dried farmyard manure and dehydrated poultry manure	Factory farming origin forbidden
Composted animal excrements, including poultry manure and composted farmyard manure included	Factory farming origin forbidden
Liquid animal excrements	Use after controlled fermentation and/or appropriate dilution Factory farming origin forbidden
Composted or fermented household waste	Product obtained from source separated household waste, which has been submitted to composting or to anaerobic fermentation for biogas production Only vegetable and animal household waste Only when produced in a closed and monitored collection system, accepted by the Member State Maximum concentrations in mg/kg of dry matter: cadmium: 0,7; copper: 70; nickel: 25; lead: 45; zinc: 200; mercury: 0,4; chromium (total): 70; chromium (VI
Peat	Use limited to horticulture (market gardening, floriculture, arboriculture, nursery)
Mushroom culture wastes	The initial composition of the substrate shall be limited to products of this Annex
Dejecta of worms (vermicompost) and insects	
Guano	
Composted or fermented mixture of vegetable matter	Product obtained from mixtures of vegetable matter, which have been submitted to composting or to anaerobic fermentation for biogas production
Products or by-products of animal origin as below: blood meal, hoof meal, horn meal, bone meal or degelatinized bone meal, fish meal, meat meal, feather, hair and 'chiquette' meal, wool fur, hair dairy products	Maximum concentration in mg/kg of dry matter of chromium (VI): 0
Products and by-products of plant origin for fertilisers	Examples: oilseed cake meal, cocoa husks, malt culms
Seaweeds and seaweed products	As far as directly obtained by: (i) physical processes including dehydration, freezing and grinding (ii) extraction with water or aqueous acid and/or alkaline solution (iii) fermentation
Sawdust and wood chips	Wood not chemically treated after felling
Composted bark	Wood not chemically treated after felling

Wood ash	From wood not chemically treated after felling
Soft ground rock phosphate	Product as specified in point 7 of Annex IA.2. to Regulation (EC) No 2003/2003 of the European Parliament and of the Council (1) relating to fertilisers, 7 Cadmium content less than or equal to 90 mg/kg of P20
Aluminium-calcium phosphate	Product as specified in point 6 of Annex IA.2. of Regulation 2003/2003, Cadmium content less than or equal to 90 mg/kg of P205 Use limited to basic soils (pH > 7,5)
Basic slag	Products as specified in point 1 of Annex IA.2. of Regulation 2003/2003
Crude potassium salt or kainite	Products as specified in point 1 of Annex IA.3. of Regulation 2003/2003
Potassium sulphate, possibly containing magnesium salt	Product obtained from crude potassium salt by a physical extraction process, containing possibly also magnesium salts
Stillage and stillage extract	Ammonium stillage excluded
Calcium carbonate (chalk, marl, ground limestone, Breton **ameliorant, (marl), phosphate chalk)**	Only of natural origin
Magnesium and calcium carbonate	Only of natural origin e.g., magnesian chalk, ground magnesium, limestone
Magnesium sulphate (kieserite)	Only of natural origin
Calcium chloride solution	Foliar treatment of apple trees, after identification of deficit of calcium
Calcium sulphate (gypsum)	Products as specified in point 1 of Annex ID. of Regulation 2003/2003 Only of natural origin
Industrial lime from sugar production	By-product of sugar production from sugar beet
Industrial lime from vacuum salt production	By-product of the vacuum salt production from brine found in mountains
Elemental sulphur	Products as specified in Annex ID.3 of Regulation 2003/ 2003
Trace elements	Inorganic micronutrients listed in part E of Annex I to Regulation 2003/2003
Sodium chloride	Only mined salt
Stone meal and clays	

As you can see, only organic fertilizers or fertilizers of natural origin are permitted in organic crop production, with the aim to preserve soil quality and avoid synthetic manufacturing. Similarly, only natural, non-synthetic plant protection products are permitted for application directly on the plant, with the exception of a few permitted synthetic substances such as mineral and paraffin oil, copper-based salts, and some minerals like calcium hydroxide, potassium permanganate, potassium bicarbonate, ferric phosphate, and lime sulphur (Appendix Table A-1). These are used only as a last resort after preventative techniques in pest, disease and weed control have been used, all in order to reduce detrimental effects on biodiversity and presence of residues in agricultural products. In regards to organically certified animal production in the EU, many variables are taken into consideration such as land area (e.g., access to open-air land per head), feed (e.g., mainly organic certified feed), breeds (e.g., adapted to environment), disease prevention (e.g., prohibition of preventive use of chemically-synthesised allopathic medicinal products), housing (e.g., sufficient space, light, ventilation), manure deposition (e.g., limited to a certain amount per hectare per year), and treatment (e.g., prohibition of mutilations leading to harm). These list only some of the many regulations that are outlined by the European Commission. Refer to the Appendix for more information regarding some of the above variables (Table A1 – Table A3).

In general, organic cropland area in EU-27 has been increasing over the past 10 years (Figure 1), and the upward trend is planned to continue since the European Green Deal aims to increase organically managed agricultural land by 25% by 2030 (European Commission, 2020a). Specifically, many Mediterranean countries in Europe like Spain, Italy, Southern France and Greece have some of the largest organic cropland areas in the EU-27 (Figure 2), representing between ~9 – 16% of the total utilized agricultural area in those countries as of 2020 (Eurostat, 2022). This demonstrates the importance of analyzing the sustainability of organic practices and the need to include these countries in the sustainability analysis of this thesis.

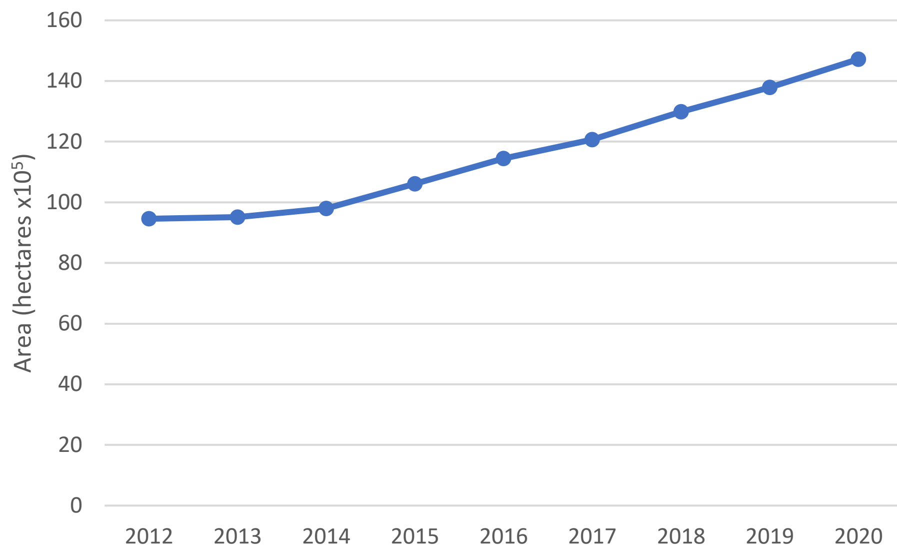


Figure 1. Organic crop area in the EU-27 from 2012-2020 (Eurostat, 2022).

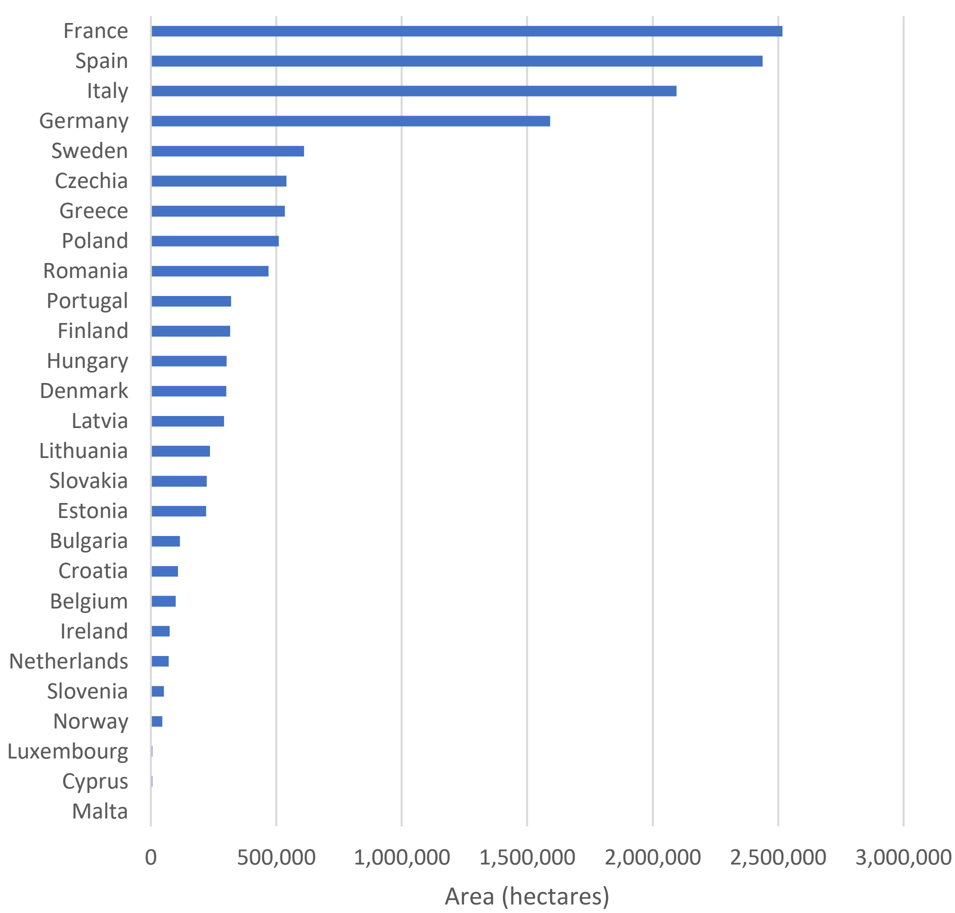


Figure 2. Organic crop area per country in the EU-27 for the year 2020 (Eurostat, 2022)**.**

The main criticism facing the advancement of OA is the yield; in general, organic yields are lower than conventional yields and, thus, would require more land to close the yield gap (De Ponti et al., 2012; Hoffman et al., 2018; Seufert et al., 2012). However, these studies also exclaim that the yield differences are highly contextual, depending on, for example, crop type, pedoclimatic conditions, and management practices. A meta-analysis on organic and conventional yield gaps by Seufert et al. (2012) found that organic fruits and oilseed crops have a lower organic-to-conventional yield ratio compared to vegetables and cereals, as do perennials compared to annuals and legumes compared to non-legumes (Figure 3). Within the cereals, maize has a significantly lower yield gap compared to other cereals like barley and wheat (Figure 3). Seufert et al. (2012) also found that organic yields were 13% lower than typical conventional when best organic practices were used, and 34% lower when organic and conventional systems were most comparable (Figure 4). They also found that applying best management practices in both systems shows better organic performance (Figure 4). This study also found that organic yields increase gradually over time due to increased soil fertility and management skills.

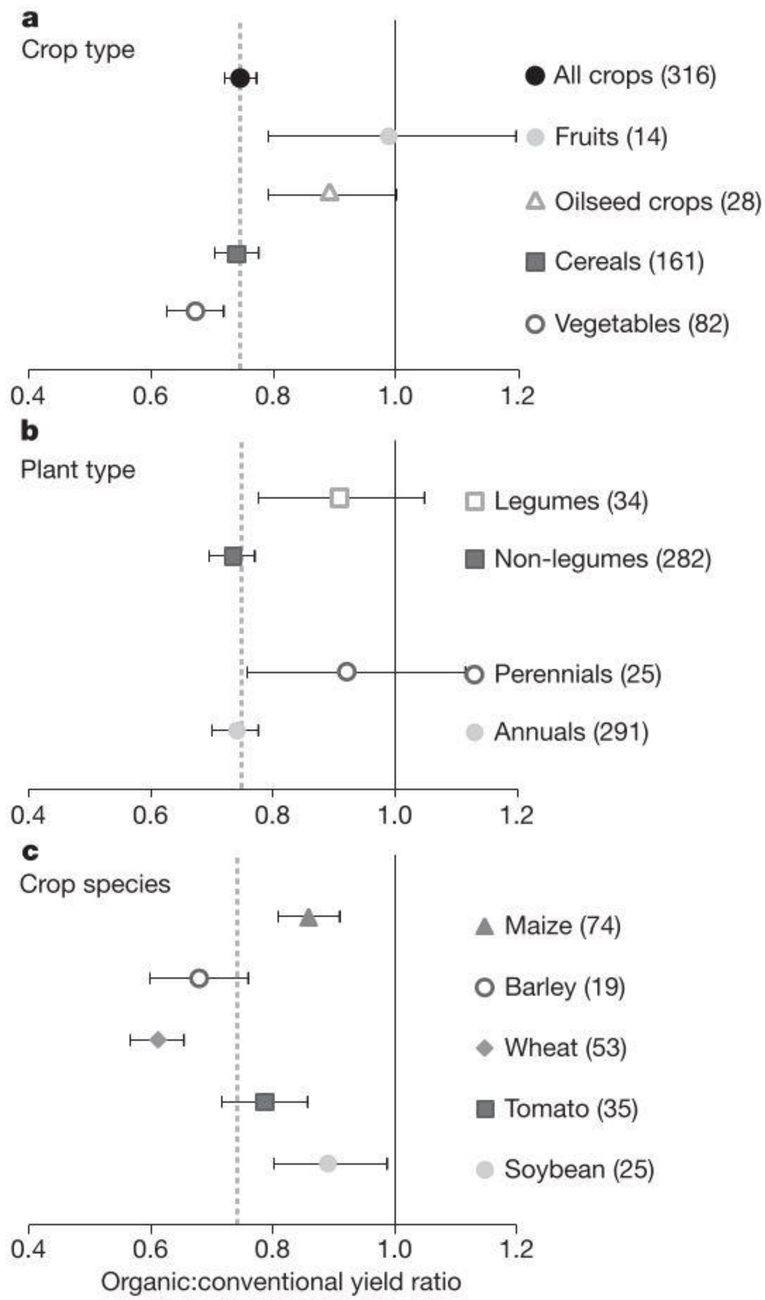


Figure 3. Effect of different crop types, plant types and species on organic-to-conventional yield ratios. Values are mean effect sizes with 95% confidence intervals. The number of observations in each class is shown in parentheses (Seufert et al., 2012).

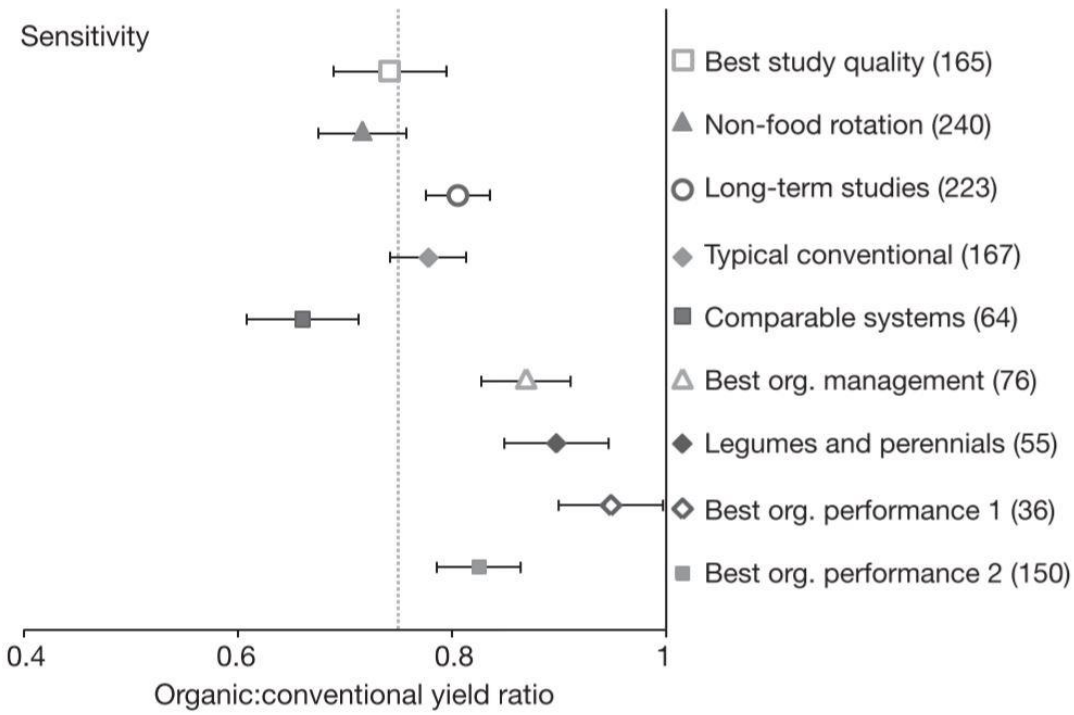


Figure 4. Sensitivity assessment of organic-to-conventional yield ratios. Values are mean effect sizes with 95% confidence intervals. The number of observations in each class is shown in parentheses (Seufert et al., 2012).

This is supported by other studies showing that yield gap approached near closure after 10-13 years of conversion from conventional to organic in a crop rotation of potato, peas, leek, barley, sugar beet and maize in the Netherlands (Schrama et al., 2018), owing to "…improved soil structure with higher organic matter concentrations and higher soil aggregation, a profound reduction in groundwater nitrate concentrations, and fewer plant-parasitic nematodes." The meta-study by Ponisio et al. (2015) found that on average organic yields were only 19.2% (±3.7%) lower than conventional yields, which was smaller than estimates in other studies. They found no significant difference in yields, "…for leguminous versus non-leguminous crops, perennials versus annuals or developed versus developing countries." Instead, the main factor that significantly influenced the yield gap was multi-cropping and crop rotation practices when applied in organic systems.

On the other hand, OA is meant to provide more ecosystem services than just the basic one of food provision, such as regulation (avoiding erosion, water cycles, nutrients, pollinators, etc.), support (biological cycles, fire prevention), and culture (landscape aesthetics). If society were to prioritize the other ecosystem services, maximizing yields may become less important, and the yield benchmark may be lowered. This argument was analyzed in a study by Wilbois and Schmidt (2019), where they state that current societal values allow for production to exceed ecologically sustainable limits, leading to the "traditional yield gap" between organic and conventional systems, but if new ecologically sustainable thresholds were set, the yield gap would shrink, showing the "true yield gap" (Figure 5). This is important for LCAs of crop and livestock products since the functional unit used is usually the mass of the product (e.g., impact per tonne of apples), thus if the yields were adjusted, the impact per mass unit would change.

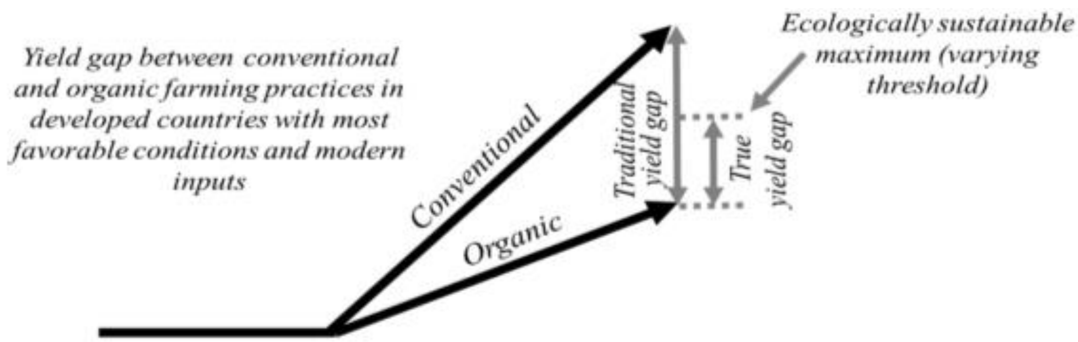


Figure 5. The true yield gap between organic and intensive conventional management shrinks when an ecologically sustainable threshold is set as a benchmark (Wilbois and Schmidt, 2019).

1.1.2 LIFE CYCLE ASSESSMENT

LCA is one of the most comprehensive and transparent tools that aims to assess damages due to the production of goods and services in three areas of protection: (1) human health, (2) ecosystems and (3) natural resources. It is internationally standardized under ISO 14040 (ISO, 2020a, 2006a) and 14044 (ISO, 2020b, 2017, 2006b) and is currently recommended by United Nations Environment Programme, UNEP (Verones et al., 2017) and the European Commission (Environmental Footprint initiative (EF), https://eplca.jrc.ec.europa.eu//EnvironmentalFootprint.html) to conduct environmental impact quantifications of products and services. EF's main goal is to provide a standardised methodology that allows environmental comparisons. Currently, EF is under the transition phase, evaluating potential methodological improvements.

During a life cycle assessment, the potential environmental impacts of products and services are evaluated over their entire life cycle. Typically, the life cycle consists of raw material extraction (also referred to as the "cradle"), production of the product, distribution, use, and end-of-life disposal phases (Figure 6). The production includes all upstream activities such as production of inputs consumed in the system, and downstream end-of-life waste processes (also referred to as the "grave") associated with the production.

Thus, a full life cycle of a product is from the cradle to the grave, where other possible iterations of life cycles can exist depending on if a product is reused, redistributed, remanufactured or recycled in its end-of-life management (Figure 6). The environmental impact of extracting all relevant inputs from the environment (e.g., crude oil, land use, ores, water) as well as all emissions into water, air and soil (e.g., nitrogen oxides and carbon dioxide) from all life cycle phases are taken into consideration.

According to the ISO standards, LCA contains four iterative phases, 1) goal and scope, 2) life cycle inventory, 3) life cycle impact assessment, 4) interpretation (Figure 7).

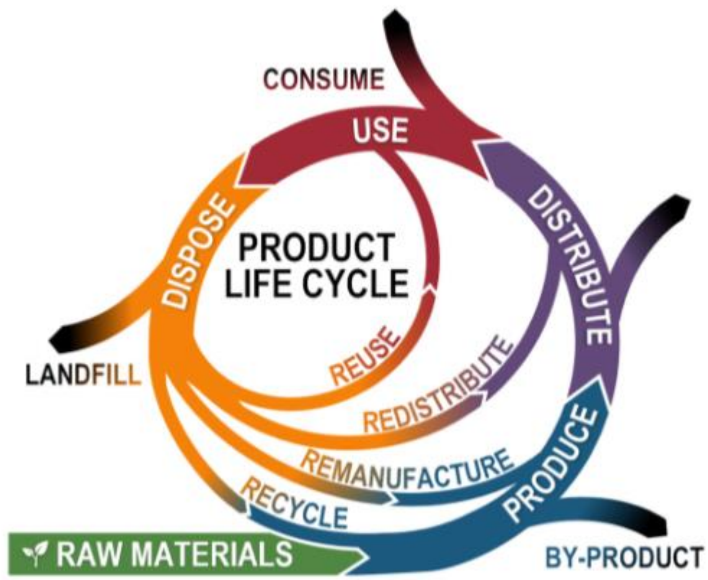


Figure 6. Scheme of the life cycle of a product (Sieverding et al., 2020).

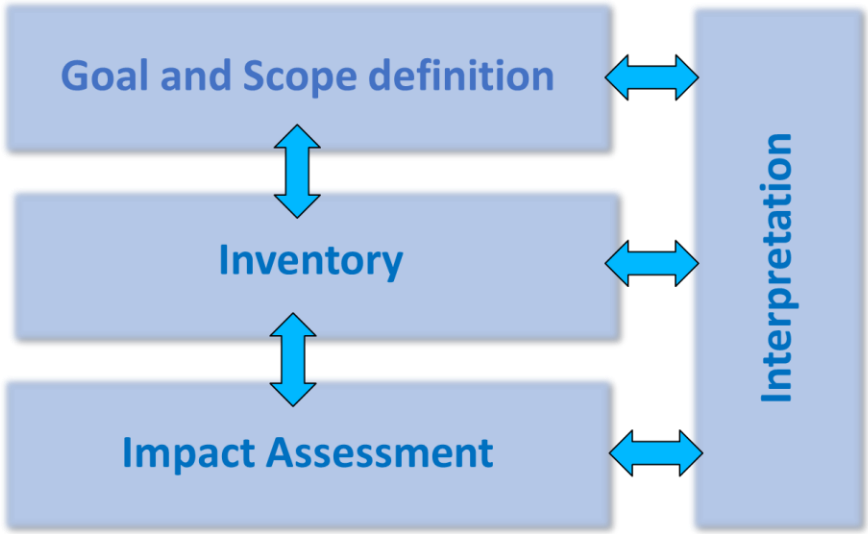


Figure 7. The four stages of life cycle assessment.

In the goal and scope phase, the features and assumptions of the assessment are defined, including what the main aim of the study is (e.g., comparison between two products) and defining the system boundaries. A clear, initial goal definition is hence essential for correct interpretation of the results. This includes ensuring that the results of the LCA study cannot be unintentionally and erroneously used or interpreted beyond the initial goal and scope. The scope should be sufficiently well defined to ensure that the breadth, depth and detail of the study are compatible and sufficient to address the stated goal. The boundaries of the system to be studied can include temporal (e.g., 1 year), spatial (e.g., in Spain) and life cycle boundaries (cradle-to-grave or cradle-to-factory or farmgate). In the present thesis, LCA system boundaries were set from cradle to farm gate since the focus of this thesis were the farming practices of organic production systems. When estimating the environmental impacts of the whole life cycle of a food product, the (farm) production stage often dominates the results, contributing 61% to food's GHG emissions (this figure changes to 81% if deforestation is included), 79% to acidification, and 95% to eutrophication and covers ~37% of the world's ice- and desert-free land (Poore and Nemecek, 2018), demonstrating the importance of deeply analyzing this stage. This means that all upstream processes of the farm are included such as raw material extraction and manufacturing (e.g., of diesel, machinery, plant protection products (PPP), infrastructure and other materials used on the farm), as well as all activities performed on the farm (e.g., fertilizer and PPP application emissions, enteric emissions, diesel combustion from machinery operations, organic residue treatment), until the product is transported to the farm gate (e.g., storage facility or slaughterhouse). This constitutes only the "raw material" and "production" stages of the normal life cycle of a product (Figure 6), where stages after the farm gate such as "distribution", "use" and "disposal" were excluded.

An example of life cycle system boundaries for crop and animal production from cradle to farm gate is shown in Figure 8, where everything within the system boundary lines are analyzed in the LCA (sourced from Nemecek et al. 2015).

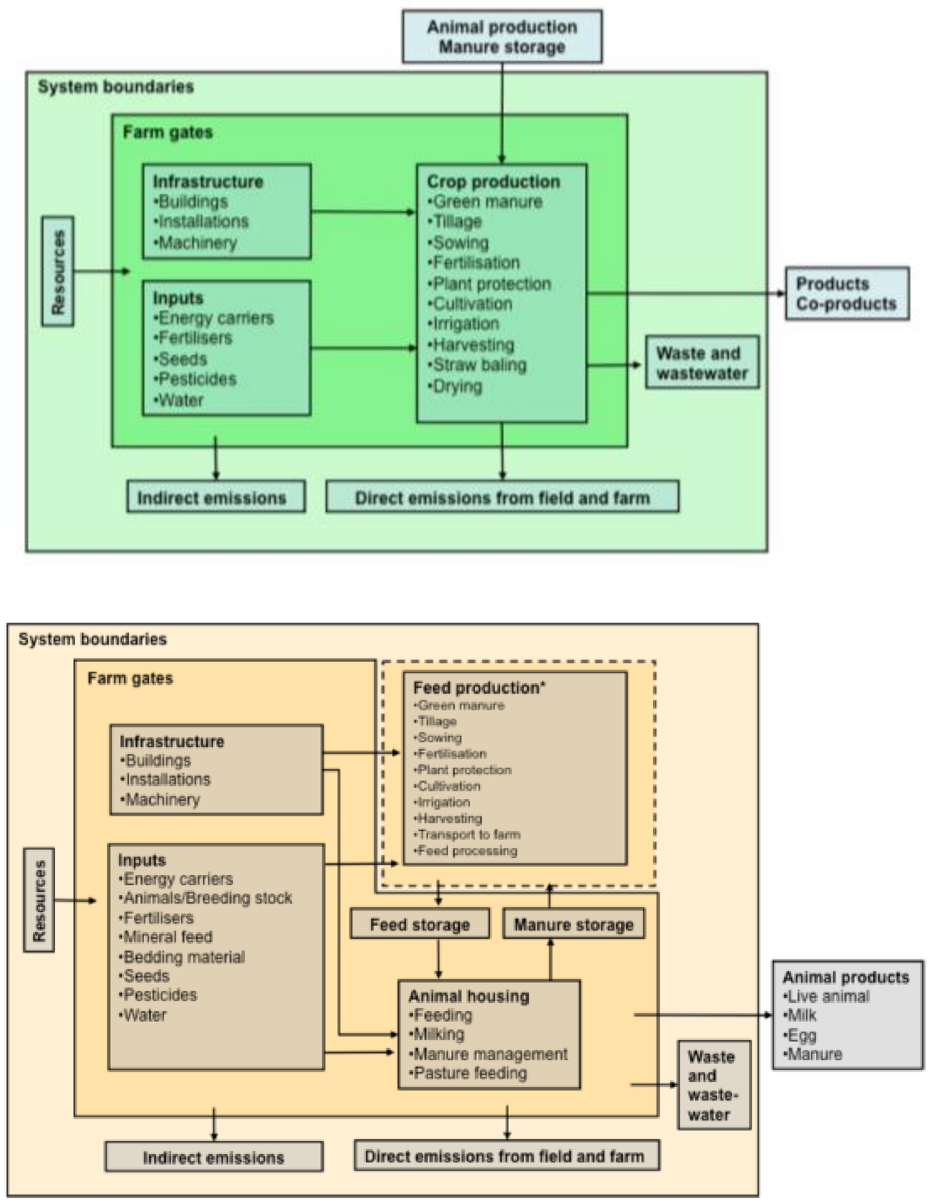


Figure 8. Typical example of life cycle system boundaries of crops and animal products (Nemecek et al., 2015).

Additionally, in the goal and scope stage, the functional unit is also defined; it is a measure of the function of the studied system and it provides a reference to which the inputs and outputs, and the final results can be referenced to. For example, the inputs, outputs and environmental impact could be quantified per kg of product if the function is to produce high yields of foodstuffs. This also allows comparability between products, where assessments can be made on a common basis with the same functions.

The second stage of LCA, the life cycle inventory stage (LCI), is where all the inputs and outputs of a product's system are quantified according to a reference flow or functional unit, hence, an "inventory" is made of this data. It involves collection of the data necessary to meet the goals of the defined study. For example, inputs may include elementary flows derived from nature, product flows and energy flows, whereas outputs may include the final product(s), emissions to air, water or soil and waste flows (See Figure 9 as an example).

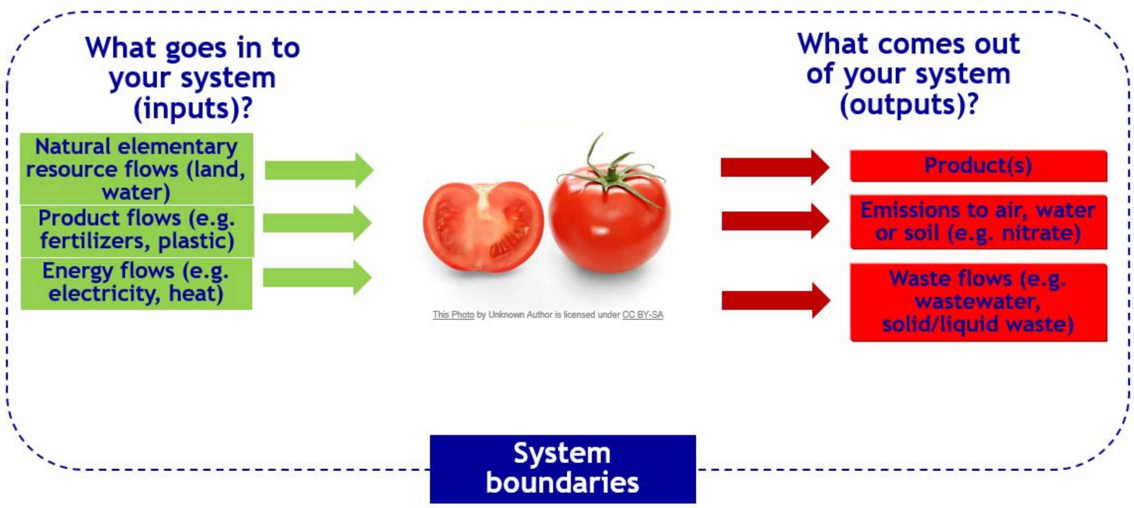


Figure 9. Scheme of the life cycle inventory stage.

The third phase of LCA, the Life Cycle Impact Assessment (LCIA) phase, is aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts of a production system. Impact models are used to calculate characterisation factors or impact factors that can be used to connect elementary flows (emissions and resource consumptions) to the corresponding environmental impacts in different categories. Each impact model quantitatively calculated the characterisation factors based on the scientific analysis of the relevant environmental processes.

Due to the proliferation of different impact models, several initiatives seek to strengthen and harmonise methods to be applied. Among these initiatives, I would highlight those conducted by the FAO-Livestock Environmental Assessment and Performance (FAO, 2020), UNEP-SETAC Life Cycle Initiative (UNEP-SETAC, 2019) and the European Platform for Life Cycle Assessment (Fazio et al., 2018b). Due to the EU scope of the thesis and the Organic-PLUS project, I followed recommendations in relation to impact assessment models to be applied from the Environmental Footprint (EF) initiative (Fazio et al., 2018b), which is derived from the International Life Cycle Data system, ILCD scheme (European Commission -- Joint Research Centre -- Institute for Environment and Sustainability, 2010) and guidance from the aforementioned initiatives. EF's main goal is to provide a standardised methodology that allows environmental comparisons. Currently, EF is under the transition phase, evaluating potential methodological improvements. Table 2 lists the current environmental impact categories to be considered and presents the recommended methods for each impact category according to the EF initiative. This table also includes level of robustness for each impact category, which gives an idea of the certainty of the method. Robustness corresponds to EF's level of recommendation, based on scientific judgement performed across the different existing methods. It ranges from level I for models and characterisation factors which are recommended for all types of life cycle-based decision support, to level III (interim), which is recommended but only with caution given the considerable uncertainty, incompleteness or other shortcomings, aspects that need to be considered when performing an LCA. Being aware of the importance of biodiversity indicators for organic production systems but lack of assessment methods we have deepened the present study by proposing a set of potential biodiversity indicators in this thesis.

Table 2. Recommended Impact categories, indicator, units, default Impact assessment models and level of robustness (Fazio et al., 2018b).

Impact category	Indicator	Unit	Recommended default impact model	Robustness
Climate change	Radiative forcing as Global Warming Potential (GWP100)	kg CO_2 eq	Baseline model of 100 years of the IPCC (IPCC, 2013)	I
Ozone depletion	Ozone Depletion Potential (ODP)	kg CFC-11eq	Steady-state ODPs as in (WMO, 1999)	I
Human toxicity, cancer effects	Comparative Toxic Unit for humans (CTUh)	CTUh	USEtox model (Rosenbaum et al., 2008)	III/interim
Human toxicity, non-cancer effects	Comparative Toxic Unit for humans (CTUh)	CTUh	USEtox model (Rosenbaum et al., 2008)	III/interim
Particulate matter/Respiratory inorganics	Human health effects associated with exposure to PM2.5	Disease incidences	PM model recommended by UNEP (Fantke et al., 2016)	I
Photochemical ozone formation	Tropospheric ozone concentration increase	kg NMVOC eq	LOTOS-EUROS (van Zelm et al., 2008) as applied in ReCiPe 2008	II
Acidification	Accumulated Exceedance	mol H^+ eq	Accumulated Exceedance (Posch et al., 2008)	II
Eutrophication, terrestrial	Accumulated Exceedance	mol N eq	Accumulated Exceedance (Posch et al., 2008)	II
Eutrophication, aquatic freshwater	Fraction of nutrients reaching freshwater end compartment (P)	kg P eq	EUTREND model (Struijs et al., 2008)	II
Eutrophication, aquatic marine	Fraction of nutrients reaching marine end compartment (N)	kg N eq	EUTREND model (Struijs et al., 2008)	II
Ecotoxicity (freshwater)	Comparative Toxic Unit for ecosystems (CTUe)	CTUe	USEtox model, (Rosenbaum et al., 2008)	III/interim
Land use	Soil quality index (Biotic production, Erosion resistance, Mechanical filtration and Groundwater replenishment	Points (Pt), Dimensionless, aggregated index of: (kg biotic production, kg soil, m^3 water, m^3g water)/ (m^2*a)	Soil quality index based on LANCA (Bos et al., 2016)	III
Water scarcity	User deprivation potential (deprivation-weighted water consumption)	kg world eq. deprived	Available Water Remaining (AWARE) in (Boulay et al., 2016)	III
Resource use, minerals and metals	Abiotic resource depletion	kg Sb eq (kg Antimony eq)	CML (van Oers et al., 2002)	III
Resource use, energy carriers	Abiotic resource depletion – fossil fuels	MJ	CML (van Oers et al., 2002)	III

In the interpretation phase, the identification of the significant issues based on the results of the LCI and LCIA phases are conducted. Identification shall be done among processes, impact categories (normalised and weighted values), potential bottlenecks, limitations and finally evaluating the initial goal and scope of the study (e.g., comparing the performance of two products) from an environmental perspective.

Table 3 provides the main substances/flows relevant to agriculture, which usually represent the major contributors for each impact category.

Table 3. Main agricultural cradle-to-farm-gate flow contributors for each environmental impact category (excluded Human Toxicity impact categories due to long list). List of substances derived from (Rosenbaum et al., 2018)**.**

Impact category	Units	Substances
Climate change	kg CO_2 eq	Carbon dioxide, CO_2. fossil Dinitrogen monoxide, N_2O Methane, CH_4
Ozone depletion	kg CFC-11eq	CFCs HCFCs
Particulate matter/Respiratory inorganics	Disease incidences	Ammonia, NH_3 Nitrogen oxides, NO_x Particulates, < 2.5 um Particulates, > 2.5 um, and < 10um Sulphur dioxide, SO_2
Photochemical ozone formation	kg NMVOC eq	Carbon monoxide, CO Sulphur dioxide, SO_2 Methane, CH_4
Acidification	mol H+ eq	Ammonia, NH_3 Nitrogen oxides, NO_x Sulphur dioxide, SO_2
Eutrophication, terrestrial	mol N eq	Ammonia, NH_3
Eutrophication, aquatic freshwater	kg P eq	Phosphorus, P
Eutrophication, aquatic marine	kg N eq	Ammonia, NH_3 Nitrogen oxides, NO_x Nitrate, NO_3
Ecotoxicity (freshwater)	CTUe	Copper Sulphur Pesticides Heavy metals Oil crude
Land use	Pt	Crop/Pasture field Occupation Peat
Water scarcity	kg world eq. deprived	Water consumption (Irrigation) Hydropower electricity
Resource use, minerals and metals	kg Sb eq	Copper Phosphate Rock Sulphur
Resource use, energy carriers	MJ	Coal Gas, natural Oil crude

1.1.3 ORGANIC-PLUS PROJECT

The work presented in this thesis is part of the Organic-PLUS project, "Pathways to phase-out contentious inputs from organic agriculture in Europe," under the European Commission's Horizon 2020 Programme (Grant agreement 774340). The overall aim of the Organic-PLUS project was "…to provide high quality, trans-disciplinary, scientifically informed decision support to help all actors in the organic sector, including national and regional policy makers, to reach the next level of the EU's organic success story" (https://organic-plus.net/). Organic agriculture is endorsed by the European Commission's Green Deal, aiming to have at least 25% of the EU's agricultural land under organic farming by 2030 (European Commission, 2020b). However, this sustainability needs to be proven, considering the different aspects included in sustainability. One of the objectives of the project was to conduct the environmental assessment of relevant contentious and alternative products and production systems studied in the Organic-PLUS project.

In particular, the environmental assessment was conducted following a life cycle perspective, therefore using Life Cycle Assessment and the recommended EF LCIA impact category methods (Table 2). However, organic production systems are overlooked in the EF initiative, which makes it challenging to assess environmental effects of converting to such production. In fact, several criticisms (Meier et al., 2015; van der Werf et al., 2020) were made on LCA studies when applied to organic production systems in particular because several aspects (e.g., biodiversity indicators, multifunctional system) may not be accounted for. Therefore, being aware of its potential, but also the limitations of the tool, it was my ambition to take advantage of the holistic vision of LCA, for both the whole production chain concept and multicriteria environmental indicators, and to contribute to improve the methodology to make it more suitable for organic production systems.

Work conducted under this task could be summarized as:

- Assessment of baseline scenarios, which contain contentious inputs currently used in organic farming, with a focus on the Mediterranean regions.
- Create calculations tools to conduct current and further environmental assessments.
- Assessment of alternatives to contentious inputs within each baseline scenarios.
- Critical analysis of LCA tools used to assess organic production systems (challenges and proposals when conducting an LCA on organic farming, datasets, emission modelling, and impact categories).

- Review state-of-the-art biodiversity indicators and propose an indicator for application in organic production systems.

Through this work conducted, many challenges were faced when developing the life cycle inventory of baseline crop scenarios, such as finding suitable inputs for plant protection products and organic fertilizers, calculating their relevant application emissions, and finding suitable crop datasets as proxies or for comparison. Therefore, it was found that the life cycle inventory of organic crops needed to be further researched.

1.2 STATE OF THE ART

Since LCA is able to quantitatively address multiple impact categories and is recommended by many international governing bodies (European Commission, UNEP, FAO), it is a suitable methodology in comparative assessments (e.g., organic vs. conventional) as some systems may perform better in some categories than others, thus offering a more comprehensive view of any burden-shifting between categories. Therefore, the main aim of this thesis was to analyse the capabilities of LCA methodology to analyze OA systems and products and ways to improve it. The following sections will explain the state-of-the-art research in the application of LCA to OA and biodiversity.

1.2.1 ENVIRONMENTAL IMPACT OF ORGANIC AGRICULTURE

Many studies have used LCA methodology to quantify the environmental impact of OA, these previous studies will be discussed here. A study by Aguilera et al. (2015a, 2015b) found that product-based GHG emissions can be reduced by 39% in fruit trees and by 36-65% in herbaceous crops when under organic management compared to conventional. Smith et al. (2019) also found that lower GHG emissions under OA were largely due to replacement of mineral N fertilizer with biological N fixation in leys, resulting in less CO_2 and N_2O from fertilizer manufacture and less N_2O per unit of production. The same was found in (Pieper et al., 2020) where organic plant-based foodstuffs had lower GHG emissions and hence climate change potential per kg of product than conventional, resulting in lower external climate costs. However, the opposite was found for animal-based products due to the higher land area per animal prescribed by organic regulations compared to conventional. Muller et al. (2017) substantiate that GHG emissions are lower for OA systems and can reduce N-surplus and pesticide use, but on the other hand uses more land area. Compared to integrated farming systems in Switzerland, OA have been found to be similar or superior in regards to ecotoxicity, biodiversity and resource conservation (Nemecek et al., 2011).

Other non-LCA, studies found that OA systems perform superior to CA in terms of increased soil organic matter due to higher soil sequestration from cover- or inter-crops and manure application (Blanco-Canqui et al., 2017; Scialabba and Mller-Lindenlauf, 2010).

Meta-studies that use LCA to model the environmental performance of OA compared to CA, found that the environmental performance of OA is not always the clear winner - its performance can be higher or lower than conventional products depending on the impact category studied and the functional unit (FU) used, such as yield or cultivated area (Clark and Tilman, 2017; Meier et al., 2015; Tuomisto et al., 2012). Tuomisto et al. (2012) found that LCAs modelling global warming potential, eutrophication of waterbodies and soil and air acidification, tend to have higher impacts in OA compared to CA per product unit but lower impacts per land area due to larger areas used in OA. On the other hand, OA products perform better in human toxicity and eco-toxicity as well as non-renewable resource depletion potential than CA products due to the fact that synthetic pesticides and mineral fertilizers are not used in OA (Meier et al., 2015; Tuomisto et al., 2012). Clark and Tilman (2017) found that OA may tend to cause more eutrophication, emit similar GHG quantities as CA, require more land, but use less energy. In general, impacts per product unit may be higher in OA compared to CA due to the higher yields in CA (De Ponti et al., 2012; Seufert et al., 2012) and significantly lower temporal yield stability in OA (Knapp and van der Heijden, 2018), but results were highly dependent crop groups and regions. However, a study by Hayashi (2013) found that the utilization of product-oriented FU's like product weight or land-oriented FU's like hectares within the context of organic conversion, must be used complementarily, because the use of one or the other would not allow the practitioner to conclude if the conversion minimized impacts per area unit *and* per product unit. In other words, using land-oriented FU will allow practitioners to work out if there have been trade-offs between impact per area unit and yield per area unit or if it had been a win-win, lose-lose situation. Using product-oriented FU will allow practitioners to work out if the conversion was efficient (low impact per product unit) or inefficient (high impact per product unit). Hence, employing a combination of both can determine if the system had trade-offs and was efficient or inefficient. Hayashi (2013) also recommended that besides the utilization of FUs, decision criteria should even be used. Specifically, decisions should be made with regard to two important criteria, minimize impacts per area unit and maximize yield per area unit.

Although these meta-studies as well as a plethora of other organic crop and animal LCA case studies exist worldwide, only a few studies discuss the limitations in applying LCA methodology to OA (Meier et al., 2017; Tuomisto et al., 2012; van der Werf et al., 2020). These studies focused mainly on the importance of including biodiversity and ecosystem indicators when assessing organic systems and the lack of functional units (other than solely yield-focused) that represent the multi-functionality of organic systems such as preserving ecosystem quality. However, these critical aspects are not only applicable to LCA for OA, but more so for agricultural LCAs in general since the same land and its surroundings would be affected by any type of land use activities. To the best of our knowledge, no publication has analyzed the limitations more specific to OA, such as the life cycle inventories of organic crop products, nor biodiversity indicators specific for organic or conventional practices. The certainty and robustness of LCA results are based both on the certainty of the life cycle inventory data collected and the life cycle impact models used, or even a combination of both, such as having available inventory data but lacking sufficient impact pathways/models for it. In these cases, focus on the LCIA phase would be important. Yet if inventory data is not available (which is often the case in organic agriculture), but impact pathways and models exist, then priority should be given to the inventory phase. Therefore, research into improving both the inventory and LCIA stage is direly needed.

1.2.2 LCA AND BIODIVERSITY

According to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), biodiversity can be defined as, "the variability among living organisms from all sources including terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are a part. This includes variation in genetic, phenotypic, phylogenetic, and functional attributes, as well as changes in abundance and distribution over time and space within and among species, biological communities and ecosystems" (https://ipbes.net/glossary/biodiversity). Therefore, biodiversity is a multi-scale concept, consisting of different organizational scales (ecosystem, species, genes), spatial scales (global, regional and local), and administrative scales (government, UN, companies, communities, farmers and land owners), all across a temporal scale (Henle et al., 2014; Wu, 2006), making it difficult to assess it. Additionally, there are multiple pressures that can cause biodiversity loss, complicating its protection, where the main five pressures include: invasive and non-native species, pollution, climate change associated with global warming, habitat loss through land use, and overexploitation (extreme hunting and fishing pressure) (IPBES, 2019). Additionally, biodiversity is important not only because of its intrinsic value, but also in the provision of ecosystem services.

Biodiversity loss has become a major environmental concern closely linked to land use impacts and unsustainable production and consumption patterns. One of the main drivers of current and projected future biodiversity loss is habitat change, as a result of land use and land use change. This is exceptionally important in agriculturally intensive regions such as Europe with nearly 50% (European Commission, 2016) land occupied by farmland, where 71% (European Commission, 2016) of this is used to feed livestock, causing 50% (Kristensen, 2003) of all species to become dependent on agricultural habitats. Agricultural practices such as nutrient input, pesticide use, field operations and field cover, are closely linked with soil quality and biodiversity. Thus, OA has become a suggested solution due to its commitment to the use of more natural and preventative agricultural techniques, and prohibition of synthetic pesticides and mineral fertilizers which have been found to affect biodiversity (Knudsen et al., 2019). Therefore, it is becoming more and more pertinent to develop and improve approaches for measuring and modeling biodiversity loss due to land use pressures, such as the land required for organic production.

In agriculture, the transformation and occupation of land is the main pressure causing biodiversity loss (IPBES, 2019). One of the main debates surrounding biodiversity conservation is whether or not we should be 'land-sparing' by reducing farm sizes through intensification, or 'land-sharing' the farm with natural habitats to create a more complex landscape. In agricultural settings, land-sharing would promote ecosystem services, whilst land-sparing would retain critical areas to protect those species that are incompatible with agriculture, showing the complementary benefits (Feniuk et al., 2019; Fischer et al., 2014; Grass et al., 2019; Valente et al., 2022). These studies also say management of landscapes is only successful if context-specific land-sparing and land-sharing measures are conducted with high spatial connectivity between them, in addition to flexible options for farmers vulnerable to growing conditions, heterogeneous markets and landscape contexts. Van der Werf et al. (2020) state that some LCA studies have assigned additional GHG emissions to organic food production due to the need for more land to compensate for low yields. This justification would therefore favour the 'land sparing' concept, where by implementing high-yield farming systems, we can spare land for nature (Fischer et al. 2014). Van der Werf et al. (2020) explain that it is difficult to predict if farmers would indeed 'spare' land if they increase intensification, or if it would encourage expansion due to higher financial gain. The cause-effect mechanisms of land use transitions are hard to predict as it is highly dependent on social behaviours. However, from an environmental perspective, it can be argued that if we favour the land sparing concept, the agricultural land would then be thought of as part of the technosphere (man-made environment, as opposed to the ecosphere, i.e., natural environment) because we are weighing the land spared higher than cultivated land, indirectly rendering any emissions or effects on agricultural land less important than the land spared. Although 'land spared' could hold more species than cultivated land, and could be weighed more, it is important to also consider agricultural land with equal weight as it represents 50% of the worlds habitable land and will continue to increase as time goes on (FAO, 2020). This presents a large problem as nature does not see nor can follow these boundaries, and any animal or resource (e.g. rainwater, soil) that comes through or is part of the agricultural land can be affected by its anthropogenic activities. This does not hold true to the agroecological principle of OA, where the farmed land should be treated as one with the ecosystem, allowing all resources, including the soil, water and animals in it to co-exist symbiotically.

The European Commission (European Commission -- Joint Research Centre -- Institute for Environment and Sustainability, 2010; European Commission, 2017, 2003) recommended LCA as one of the main methods to estimate and compare the environmental impacts of products, and the FAO-LEAP Partnership (FAO, 2020) also recommended LCA especially for biodiversity impacts due to livestock land use. This Partnership aims to provide guidelines and recommendations on which indicators could be suitable to account for the effects of livestock activity on biodiversity. Furthermore, an extensive review of biodiversity indicators in European livestock science by (Kok et al., 2020), found that LCA methodology is suitable for estimating biodiversity loss in livestock production chains as it includes all stages of production including feed production. This is particularly important because the majority of terrestrial biodiversity loss in livestock systems is often attributed to feed production (Leip et al., 2015). Yet, Biodiversity indicators are not often reported in many LCAs of organic products as there is no consensus on which model to use.

Biodiversity was found to be one of the most important and distinguishing indicators between organic and conventional systems in LCA (van der Werf et al., 2020) thus, this aspect was addressed in this thesis. For example, OA systems have been found to have higher species richness at field level than their conventional counterparts (Bengtsson et al., 2005; Hole et al., 2005). More recent analyses of species richness and abundance illustrated significant positive effects of OA at the field scale, but to a much lower extent when expanded to farm scale (Nascimbene et al., 2012; Schneider et al., 2014). Nevertheless, negative effects of high pesticide applications and mineral fertilization on species richness and abundance, and positive effects of hedges and other unproductive habitats, were widespread (Lüscher et al., 2017). Furthermore, a review of 94 studies concluded that OA increases species richness at field level by ~30% compared to conventional, where the result has been consistent over the last 30 years of peer-reviewed studies (Tuck et al., 2014).

Recent developments made by the UNEP-SETAC Task Force resulted in the recommendation of global LCA characterization factors (Chaudhary and Brooks, 2018). This model calculates land use intensity-specific global characterization factors for biodiversity damage potential (BDP) for five broad land use types (managed forests, plantations, pasture, cropland, urban) under three intensity levels (minimal, light, and intense use) in each of the 804 terrestrial eco-regions. This method is excellent for high-level hotspot analysis at the ecoregion level. However, it cannot distinguish between organic and conventional land use practices, and lumps together all types of land use classes into one "cropland" or "pasture" class, and, hence, do not reflect the real impact of the activities assessed. The aggregation of land use classes into broad classes is often a consequence of using models that rely on secondary data sources. Therefore, it is essential to use characterization factors that can distinguish between farming practices when performing LCA's of OA products, but would require much more data. Though this model is recommended by UNEP-SETAC, it has not been tested for its feasibility.

The study by Kuipers et al. (2021), also applies the countryside-SAR approach, but integrates fragmentation effects, using the species-habitat relationship (SHR). It provides a set of characterisation factors were developed for 702 terrestrial ecoregions, four land-use types (urban, cropland, pasture, forestry) and four vertebrate taxonomic groups (birds, reptiles, amphibians, mammals, plus the aggregate of these groups). This model may be recommended in the upcoming guidance report by the Global Life Cycle Impact Assessment Method (GLAM) Taskforce (https://www.lifecycleinitiative.org/category/glam/), supported by United Nations Environment Programme (UNEP) and the Society of Environmental Toxicology and Chemistry (SETAC). They are working on improving the Kuipers et al. (2021) model to apply it across all impact categories, in order to upscale regional or local losses (PDF) to global extinctions in a comparable and consistent manner. In other words, they would recommend to use the same biodiversity loss model in each impact category that would feed into the Ecosystem Quality Area of Protection endpoint. This would be useful especially for species that are more globally threatened with extinction (e.g. endemic species, small-ranged species, critically endangered species) than other species (e.g. widespread species, least concern species). However, as mentioned in Chapter 3, top-down models may not be suitable for local/specific-contexts, and more suitable for high-level hotspot analysis along the value chain. Care must be taken when integrating the biodiversity model into existing indicators and using them for endpoint analysis, in terms of double counting or impact dilution. Although research is pushing ahead to test and address the "new" version of the Kuipers et al. (2021) model, the performance of the current model has not been tested, to the best of my knowledge.

Regarding the biodiversity LCIA models that can distinguish between organic and conventional agriculture, only five exist (Jeanneret et al., 2014; Knudsen et al., 2017; Koellner and Scholz, 2008; Mueller et al., 2014; Schryver and Goedkoop, 2010).

The model proposed by Schryver and Goedkoop (2010) estimates the relative change in plant species richness for land occupation compared with a reference situation - the semi-natural woodland that would occur without human interference. The limitations of this model include its geographical coverage (specific to the UK) and the use of field edges of intensive farms as a proxy for organic arable areas, and field centers as conventional areas.

Jeanneret et al. (2014) does not provide specific CFs for OA, but can account for differences between relevant land use practices such as intensive or extensive pesticide and fertilization use. However, this model is only valid for arable and grassland systems in Switzerland and surrounding regions, and would require more specific data collection for other regions.

Knudsen et al. (2017), Koellner and Scholz (2008), Mueller et al. (2014) were the only other studies found that provided CFs that distinguish between organic and conventional agriculture and are valid over a larger region. A limitation of the first two aforementioned models is the use of secondary data from different studies, which use different sampling methods. Robust and reliable CFs should be validated against or better yet, based on field data and national case studies (Souza et al., 2015).

Knudsen et al. (2017) filled this gap by developing CFs for organic and conventional agricultural production, based on standardized sampling of plant species richness in organic and conventional farms across six countries in Europe within the temperate broadleaf and mixed forest biome and hence, would be a well recommended method for calculating plant biodiversity impacts for OA in that biome. The data covered Austria, Germany, Switzerland, France, Hungary and Wales. Characterization factors were developed for arable crops, mixed pastures, grass-dominated pastures and hedges using vascular plants as a proxy for biodiversity. The six case study areas provide a good representation of variations in the biome.

However, the high site-specificity of these CFs make them inapplicable to other biomes like the Mediterranean and their specific crops like olives and vineyards. The Mediterranean is the most plant biodiverse biomes in the world outside of the tropics (Cowling et al., 1996; Gerstner et al., 2017; Rundel et al., 2016), hence why this thesis aimed to expand CFs for this biome.

1.3 MOTIVATION AND OBJECTIVES OF THE THESIS

Land managed using organic practices has been on the rise due to its use of more natural and preventative techniques with the aim to conserve the environment. However, it is not clear whether organic agriculture can actually reduce environmental impacts as the LCA methodology used to evaluate impacts have many methodological limitations in its ability to model the practices. Therefore, this thesis aimed to answer one important and overarching research question:

How can LCA be improved in order to accurately and comprehensively account for the environmental impact of organic agricultural systems?

Through the revision of state-of-the-art research in organic agriculture and LCA in the above sections, many gaps were found specifically in the LCI of organic crops, especially when attempting to build LCIs for organic food products in the Organic-PLUS project (Section 1.1.3). When researching how to overcome the challenges related to the lack of inventory data, we found that, to our best knowledge, no previous studies have analyzed the life cycle inventory modelling of organic food products. The LCI stage is one of the main determinates in the reliability and completeness of the final life cycle impact results of the product(s) (in addition to the life cycle impact stage), hence the importance to study this stage. We also found that the LCIA stage could also be further developed, where one of the main indicators that distinguishes organic from conventional agricultural systems is biodiversity loss. However, as mentioned in the aforementioned state-of-the-art sections 1.2.2, research is still needed regarding the testing of currently recommended models, and to understand which models may be more suitable for certain contexts like organic agriculture. In addition, the Organic-PLUS project called for the development of biodiversity indicators for organic agricultural land use, thus, research was done to decide which indicator may be more suitable and, furthermore, use it to develop characterisation factors for organic crops in highly diverse biomes like the Mediterranean. Therefore, this doctoral thesis aims to answer the research question posed above by focusing on improving the life cycle inventory stage and the life cycle impact assessment models for biodiversity loss through the following objectives and corresponding sub-research questions:

1. Critical analysis of state-of-the-art organic crop LCI datasets, analyzing the gaps and suggesting improvements.
    a. What are the challenges in state-of-the-art life cycle inventory modelling of organic food products?

    b. How can LCI modelling be improved?

2. Enhancing life cycle impact assessment methodology for biodiversity assessments due to agricultural land use.
    a. What are the challenges and strengths of currently recommended LCIA biodiversity loss models for evaluating the environmental impact of food products like livestock products?
    b. How can currently recommended LCIA biodiversity loss models be used in different spatial modelling contexts, like top-down and bottom-up scaling approaches?
    c. What further research is required to improve these models?
3. Develop characterization factors for organic and conventional agricultural land use types in the European Mediterranean biome using bottom-up modelling techniques.
    a. Using the findings from objective 2 above, what bottom-up model would be most suitable to develop characterization factors for organic and conventional agricultural land use types?
    b. What is the potential species loss of organisms due to organic and conventional agricultural land use types for European Mediterranean crops like olives, vineyards and cereals?
    c. What further research is required to improve this model?

CHAPTER 2

CRITICAL ANALYSIS OF ORGANIC CROP LIFE CYCLE INVENTORIES

This chapter has already been published as:

Montemayor, E., Andrade, E.P., Bonmatí, A., Antón, A., 2022. Critical analysis of life cycle inventory datasets for organic crop production systems. *International Journal of Life Cycle Assessment*. 27, 543–563. https://doi.org/10.1007/s11367-022-02044-x

2.1 ABSTRACT

Organic agriculture has gained widespread popularity due to its view as a more sustainable method of farming. Yet OA and conventional agriculture (CA) can be found to have similar or varying environmental performance using tools such as life cycle assessment (LCA). However, the current state of LCA does not accurately reflect the effects of OA, thus the aim of the present study was to identify gaps in the inventory stage and suggest improvements.

This chapter presents for the first time, a critical analysis of the life cycle inventory (LCI) of state-of-the-art organic crop LCIs from current and recommended LCA databases ecoinvent and AGRIBALYSE®. The effects of these limitations on LCA results were analyzed and detailed ways to improve upon them were proposed.

Through this analysis, unrepresentative plant protection product (PPP) manufacturing and organic fertilizer treatment inventories were found to be the main limitations in background processes, due to either the lack of available usage statistics, exclusion from the study or use of unrepresentative proxies. Many organic crop LCIs used synthetic pesticide or mineral fertilizer proxies, which may indirectly contain OA prohibited chemicals. The effect of using these proxies can contribute between 4 – 78% to resource and energy-related impact categories. In a foreground analysis, the fertilizer and PPP emission models utilized by ecoinvent and AGRIBALYSE® were not well adapted to organic-authorized inputs and used simplified modelling assumptions. These critical aspects can be transferred to respective LCAs that use this data, potentially yielding unrepresentative results for relevant categories. To improve accuracy and to contribute novel data to the scientific community, new manufacturing LCIs were created for a few of the missing PPPs, as well as recommendations for fertilizer treatment LCIs and more precise emission models for PPPs and fertilizers.

The findings in the present chapter add much needed transparency regarding the limitations of available OA LCIs, offers guidance on how to make OA LCIs more representative, allow for more accurate comparisons between conventional and OA, and help practitioners to better adapt LCA methodology to OA systems.

2.2 INTRODUCTION

In the life cycle inventory stage (LCI), data collection and modelling of the system is carried out in line with the goal and scope of the study. This stage typically demands the most time and effort in an LCA, as all the inputs and outputs in the system need to be quantified per a reference flow or functional unit. The quality of the data in the inventory is a main determinate in the reliability and completeness of the final life cycle impact results of the product(s). LCA databases such as ecoinvent (referred to as EI hereafter) (Wernet et al., 2016) are widely used and accessible as background and foreground inventory data in LCA studies, along with other important agricultural databases such as AGRIBALYSE® (referred to as AG hereafter) (AGRIBALYSE, 2020) and ESU World Food LCA database (ESU, 2012). For example, foreground inventory data would encompass all the inputs and outputs required to produce 1 tonne of tomatoes as the product, and the background data for this may include fertilizer or diesel production processes. To the best of our knowledge, no publication has analyzed the inventory limitations more specific to OA, such as the life cycle inventories of organic crop products. Given the planned increase in OA in Europe, it is pertinent that the inventory stage is critically examined. Critical limitations on the inventory level within datasets in databases such as EI or AG can be potentially transferred to any respective LCA study that uses them, showing the importance of analyzing state-of-the-art LCA databases and their effects on LCIA results.

Only a few studies discuss the limitations in applying LCA methodology to OA (Meier et al., 2017; Tuomisto et al., 2012; van der Werf et al., 2020). These studies focused mainly on the importance of including biodiversity and ecosystem service indicators when assessing organic systems and the lack of functional units (other than solely yield-focused) that represent the multi-functionality of organic systems such as preserving ecosystem quality. However, these critical aspects are not only applicable to LCA for OA but more so for agricultural LCAs in general since the same land and its surroundings would be affected by any type of land use activities. Therefore, this study presents a novel in-depth critical analysis of the life cycle inventory (LCI) choices of available OA crop datasets and how these limitations can affect life cycle impact assessment (LCIA) results and, furthermore, specific ways to improve these limitations. Practitioners should be fully aware of the limitations presented here, as well as suggestions on how to advance in these aspects.

This study aims to improve the preparation of LCI's for organic crop production systems, where the specific goals were:

1. Explore and document currently available state-of-the-art crop LCI data for OA
2. Analyze gaps in existing datasets and their possible consequent effects on LCA results
3. Suggest recommendations for improving OA LCI datasets

2.3 METHODS

In order to assess the accuracy of current organic crop LCIs, existing databases were searched for organic crop datasets, then background data and emission modelling were analyzed, with special emphasis on fertilizers and plant protection products (PPPs).

2.3.1 EXISTING ORGANIC AGRICULTURAL DATASETS

The Global LCA Data access network (GLAD, https://www.globallcadataaccess.org/) was used to find existing European LCA organic crop datasets. The databases ecoinvent v3.8 (Wernet et al., 2016), AGRIBALYSE® v3.0 (AGRIBALYSE, 2020), ESU (ESU, 2012) and Agri-footprint v5.0 (van Paassen et al., 2019) were found to be the most comprehensive and up-to-date agricultural LCA databases for crops in Europe. However, not many datasets are available for a wide range of organic products nor geographic locations for use as background or foreground data, with only ecoinvent v3.8, AGRIBALYSE® v3.0 and ESU being the only databases that contain organic datasets for crop and/or animal products in Europe, where a summary of the datasets can be found in Table 4. Crops ranged from cereals, to vegetables and perennial fruits. Therefore, a critical analysis of organic crop datasets from ecoinvent v3.8 and AGRIBALYSE® v3.0 were the focus of the present study, excluding animal and animal feed products. The EI system model "allocation, cut-off by classification" was used for the critical analysis. The ESU database was not included due to its similarities with ecoinvent (both based on data in Switzerland), the extra cost required for download, and the fact that it is only compatible with background databases ecoinvent v2.2 or v3.2, whereas in this study v3.8 was used. The organic crop datasets in EI and AG are publicly available for use, hence critical issues could be passed on to any respective studies that use these datasets, showing the importance of the present study.

Table 4. State-of-the-art LCA databases that include organic agricultural products.

Database	Crop type					Livestock		Country	Year
	Cereals	Vegetable / legumes	Fruit	Oil Seed	Inter crop	Animals	Feed		
ecoinvent v3.5	11	3	0	1		0	7 [a]	Switzerland	1996-2011[b]
AGRIBALYSE® v3.0	47	8 / 28	7	5	14	40	12	France	2011-2015
ESU	12	30	16	0		16	15	Switzerland	1997 - 2012[c]

[a] excluding nested datasets and conventional soy production

[b] most up to 2002

[c] most up to 2009

Since a particular trait of organic production systems is the use of 'natural' PPPs and fertilizers (as opposed to synthetic or mineral ones used in conventional production systems), the background and foreground processes relevant to PPP products and fertilizers were the main focus of the present study. Thus, a selection of organic crops from EI and AG that had PPPs and fertilizers in their LCIs was made. Moreover, only those datasets that were representative of the country or region were selected. Some organic crop datasets in AG represent a typical case and are not representative of a national or regional average (such as barley, winter wheat, fava, wine grape and soybean). We wanted to analyze those datasets that were representative at a larger scale, since the aim of the present study is to analyze LCI of OA in general, thus those "typical cases" were excluded from the present study. There were two datasets for organic sunflower available, one for the Gers region and one for Pays de la Loire. The Gers dataset was chosen because it contained more fertilizer inputs for us to analyze. In addition, survey data from organic farms in the European Horizon 2020 project Organic-PLUS (Grant agreement 774340) (called ORG+ hereafter) helped us to identify other requirements for background PPP and fertilizer LCI data. The final selection of organic crops and their relevant data from EI, AG and ORG+ analyzed in this study are listed in Table B-1. It must be noted that for the orchards and vineyards in AG, the main production stage, "full production" was assessed, excluding the stages seedling, plantation and destruction, and first production years. This stage had the highest impacts out of all the stages and spanned most of the lifetime of the orchard, thus allowed us to focus on the main inputs required for cultivation.

In summary, the organic crop LCIs were analyzed in regards to two main aspects, the PPPs and fertilizers used in the LCIs, thus the Results and Discussion were divided into these two main areas. They were analyzed according to their compliance with European OA regulations (European Commission, 2008a), representativeness of background fertilizer and PPP manufacturing datasets and representativeness of foreground emissions modelling for fertilizer and PPP application.

The data quality of relevant PPP and fertilizer background datasets were discussed using a weighted average data quality rating (W-DQR). The indicators used to calculate the DQR were reliability, completeness, temporal and geographical correlation, and further technological correlation using the pedigree matrix approach from Weidema (1998), and modified in Weidema et al. (2013, refer to pg. 76 for explanation) and the Product Environment Footprint, PEF (European Commission, 2017). A score of 1 means excellent data quality, 2 good quality, 3 fair quality and 4-5 poor quality. The initial scores for each LCI dataset were provided by the LCA database providers. Using these scores, a W-DQR was calculated in the present study by first averaging the initial DQR of each input/output within a dataset (e.g., electricity in the kaolin LCI, $DQR_{electricity}$ = 3), then weighted each of these DQRs by its contribution to the total impact for each category (e.g., 47% in climate change), then averaged across all categories to get a final W-DQR (e.g., 3.0, fair). According to the PEF data quality requirements (European Commission, 2017), 90% of environmentally relevant data within an LCI shall be at least of fair quality, hence the importance of using a W-DQR average. Details on the information used to calculate the average W-DQR can be found in Supplementary material of the published article Montemayor et al. (2022;Tables S4 – S20).

2.3.2 EFFECT OF CRITICAL ASPECTS ON LCA RESULTS

To demonstrate how and to what degree the identified limitations in organic crop LCI datasets, namely the choices in PPP and fertilizer datasets and their on-field emissions, affect LCA results, life cycle impact assessments were conducted using the Environmental Footprint v3.0 (EF) characterization method (Fazio et al., 2018a) as implemented in the software SimaPro v. 9.1.1.7. The midpoint impact categories climate change potential (CCP, kg CO2 eq), ozone depletion potential (ODP, kg CFC-11 eq), terrestrial acidification (ADP, mol H+ eq), freshwater eutrophication (FEP, kg P eq), marine eutrophication (MEP, kg N eq), resource energy carrier use (REP, MJ), and resource mineral and metal use (RMP, kg Sb eq) were selected because of their relevance to agricultural production and energy-related processes. Respiratory inorganics and water scarcity midpoint impact categories were not analyzed due to insufficient data flows in the AG database. Toxicity categories were also not included due to the lack of impact characterization factors for many PPPs used in the datasets (discussed in the Results and Discussion).

Since the focus of the study was to demonstrate to what degree the limitations in PPP and fertilizer datasets and their on-field emissions have on the LCA results of each crop, a contribution analysis of each input was carried out. Inputs included machinery, on-field emissions, land and water use, fertilizer production, PPP production, transport, seed production, mechanical weeding, infrastructure and transport of workers, where applicable. The absolute value results were not reported as comparing impacts between products was not the aim of our study.

2.3.3 RECOMMENDATIONS FOR IMPROVEMENT

Recommendations on how to improve aspects of the LCI stage in application to OA were suggested, in order to reflect OA practices more accurately and to allow a fairer comparison between OA and CA. In respect to improving PPPs, a search was conducted in Google Scholar to find studies that could model LCIs for microbial-derived products used as PPPs in OA, such as *Bacillus subtilis, B. thuringiensis* and Spinosad, using the keywords "life cycle assessment" AND "inventory" AND "microbial products". The study by Harding (2008) and Harding and Harrison (2016a, 2016b) was found to be the most relevant and practical study that provided a tool to calculate LCIs for microbial products called, the CeBER Bioprocess Modeller (Centre for Bioprocess Engineering Research at the University of Cape Town, Department of Chemical Engineering). This model estimates the life cycle inventory needs of industrial microbial processes such as material and energy balances and equipment volumes and utility needs. This would include both the microbial growth and product formation as well as any downstream processing such as separation and filtration techniques.

Additional LCIs were suggested for other types of PPPs that already had available LCI datasets (Bordeaux mixture, copper oxide, copper sulphate, essential plant oils, kaolin, pyrethrin) by searching in the databases EI or AG, or if only their precursors were available in EI or AG, the proper ratios were suggested (which was the case for mineral oil, and potassium soap). Other PPPs such as chitosan and neem oil did not have any available LCI datasets, thus new ones were suggested by searching Google Scholar for studies that supplied data regarding their industrial manufacturing, resulting in Pighinelli (2019) and Said Al Hoqani et al. (2020) for chitosan and (Kumar et al., 2021) for neem oil.

In terms of suggestions for improving organic fertilizer emissions modelling used in EI and AG, the meta-study by Andrade et al. (2021) was used to determine which model may be more sufficient, as well as expert opinion (Angel Avadí, French National Institute for Agricultural Research, personal communication). Specific PPP emission modelling problems with copper can be found in the Results section 2.4.1.2, as its explanation was more suitable for the Results.

2.4 RESULTS

2.4.1 CRITICAL ANALYSIS OF PPPS USED IN ORGANIC DATASETS

2.4.1.1 BACKGROUND PPP MANUFACTURING

Upon inspection of the LCIs for organic crops in EI and AG (Table B-1), the relevant PPP manufacturing datasets that are available in LCA databases include copper oxide, copper sulphate, sulfur, and kaolin (Table 5), which are some of the most prevalent ones used in OA. The only biological control agent (BCA) that had some input regarding its manufacturing was *Trichogramma* in the EI maize crop dataset, where the electricity required for manufacturing was accounted for. Ecoinvent stated that no further details on *Trichogramma* could be incorporated due to data confidentiality.

Furthermore, it was found that several of the PPPs were only inventoried as output emissions to soil, without having inventoried them as inputs. This was largely due to a dire lack of manufacturing LCIs, especially for botanical PPPs and BCAs (Table 5). Although this allows for transparency regarding the PPPs that were actually used, no mass balance was achieved. For example, the botanical and microbial derived PPPs Rotenone, Pyrethrin and Spinosad were used in organic crops apple, peach and grape in AG (inventoried only as output emissions), but no manufacturing datasets were available for them. Thus, impacts regarding their manufacturing would be excluded from any assessment that use these crop datasets from these databases. It is recommended to include them as inputs in the LCI even as "empty" processes for greater transparency to users, with a disclaimer noting that the inventory is unknown. Through the ORG+ project, it was found that many BCAs were used as natural insecticides in the cultivation of aubergine and tomatoes and botanical PPPs, such as Pyrethrin or plant essential oils are also widely used in organic agricultural pest management (Andrivon et al., 2019, a report from the ORG+ project).

Table 5. List of plant protection products used in organic crop cultivation in Europe and corresponding availability of manufacturing datasets and data quality information.

Type	PPP / CAS No.	Use(s)	Manufacturing dataset available? – Database?	Average W-DQR, weighted by impact contribution to total
Metal/Mineral-based	Copper gluconate / 527 09 3	Fungicide	No	
	Copper oxide / 1317-38-0	Fungicide	Yes - ecoinvent	$W\text{-}DQR_{CuO}$ = 4.67 (i.e., poor) across all processes. $W\text{-}DQR_{Cu}$= 4.8 (i.e., poor)
	Copper oxychloride / 1332-40-7	Fungicide	No	
	Copper sulphate / 7758-98-7	Fungicide	Yes- ecoinvent	W-DQR= 3.26 (i.e., fair)
	Kaolin (aluminium silicate) / 1332-58-7	Repellent	Yes- ecoinvent	W-DQR = 3.0 (i.e., good)
	Lime sulphur / 1344-81-6	Acaricide, Fungicide, Insecticide	No	
	Paraffin oil / 8042-47-5	Acaricide, Insecticide	Yes- ecoinvent	W-DQR = 3.57 (i.e., poor)
	Potassium hydrogen carbonate / 298-14-6	Fungicide	No	
	Potassium soap	Insecticide	No	
	Sulphur / 7704-34-9	Acaricide, Fungicide, Repellent	Yes- ecoinvent	W-DQR = 2.4 (i.e., good)
Botanical	Cinnamon oil (a.i. cinnamaldehyde) / 104-55-2	Repellent	Yes – AGRIBALYSE ® 3.0	Proxy used: Conventional vanilla production, Madagascar, ecoinvent v3. $W\text{-}DQR_{Van}$ = 1.84 (i.e., very good), reported DQR_{Van} = 2.7 (good)
	Citrus oil (a.i. limonene active ingredient) /5989-27-5	Fungicide, Insecticide	No	
	Eucalyptus oil (a.i. 1, 8 – cineole) / 470-82-6	Pesticide	No	
	Neem oil (a.i. azadiractin) / 11141-17-6	Insecticide	No	
	Oregano essential oil (a.i. carvacrol) / 499-75-2	Anti-microbial, Insecticide	No	
	Pyrethrin / 8003-34-7	Insecticide	Yes - ecoinvent	W-DQR = 3.4 (i.e., fair)
	Thyme essential oil (a.i. thymol) / 89-83-8	Fungicide	Yes - AGRIBALYSE ®	Proxy used: Conventional mint production in India. Reported DQR = 2.7 (i.e., good)
	Rotenone / 83-79-4	Insecticide	No	
Micr-	*Bacillus subtilis* / 68038-70-0	Bactericide, Fungicide	No	

	Bacillus thuringiensis / 68038-71-1	Insecticide	No
	Nesidiocoris tenuis (predatory insect)	Insecticide	No
	Reynoutria sachalinensis extract (giant knotweed)	Fungicide	No
	Spinosad / 168316-95-8	Insecticide	No
	Trichoderma harzianum / 67892-31-3	Insecticide	No
	Trichogramma pretiosum / 41198-08-7	Insecticide	No

In regards to whether the crop datasets follow the EU regulations for organic production (European Commission, 2008), EI datasets followed strictly with OA principles, in that only organic-authorized PPPs were used. On the other hand, AG applied a general rule to use the "pesticide, unspecified" background dataset from EI as a proxy for unavailable PPP manufacturing datasets, and in the case of organic crops, this was a proxy for the insecticide Spinetoram, an analogue of Spinosad (Grasselly et al., 2017). This "pesticide, unspecified" manufacturing dataset represents a European average of all 78 synthetic PPPs, some of which are not authorized in European OA regulations, such as glyphosate (European Commission, 2008a), hence indirectly including impacts from synthetic PPP manufacturing. Petrol was also used as a proxy for mineral oil production and low voltage electricity was a proxy for *Bacillus thuringensis* production, which may or may not be better than not including it at all, but more adequate manufacturing datasets are needed.

Additionally, Rotenone is no longer permitted in OA in Europe, with its final authorization withdrawn in 2011 (European Commission, 2008b). In AG v1.3 the reference period for all crops and animal products, was from 2005 – 2009, thus Rotenone was still permitted in France during that time period. Therefore, if one wishes to use these datasets, it is important to check if the reference period and the PPPs inventoried are similar to the system under investigation and follows local OA regulations.

In respect to the data quality for those PPPs with available manufacturing datasets (Table 5, refer to the supplementary material in the publication Montemayor et al. (2022) for detailed calculation of DQRs), kaolin and sulphur were found to have good data quality ratings between 2 and 3. Copper oxide had poor W-DQR (4.8, i.e., poor) mainly due to the market for copper metal production; this process contributes to >90% of the total impact of copper oxide, hence demonstrating its relevance and importance. Specifically, the completeness, temporal and geographical correlation, and further technological correlation, had poor quality ratings that should be improved. Copper sulphate had fair W-DQR due to the poor quality of the copper oxide manufacturing dataset nested within that dataset, accounting for 64 – 99% of the total impact across all categories. Paraffin oil had a poor W-DQR (3.6) due to the poor quality of the chemical factory data (4.8) and fair quality of the heat data from sources other than natural gas (3.2). Specifically, the chemical factory data had poor reliability, completeness, temporal and geographical correlation and further technological correlation, whereas the heat data had poor ratings only for the first three indicators. Therefore, the aforementioned datasets do not comply with the PEF data quality requirements (European Commission, 2017) where 90% of environmentally relevant data within an LCI shall be at least of fair quality.

Thyme and cinnamon production had good W-DQR's (both 2.7), however, they both used proxies for their production, which in reality would result in a very low DQR. The thyme in particular uses a conventional mint proxy cultivated in India, which would not be a suitable proxy for European or organic contexts, as some of the inputs used are not permitted in Europe nor in organic systems, in addition to the fact that thyme and mint can be grown in Europe. Cinnamon and vanilla on the other hand, cannot be grown in European climates, thus, vanilla could be considered a good proxy. Therefore, more research is needed to improve the DQR of these existing datasets.

In regards to more specific organic pest management techniques, OA focuses mainly on preventative measures that relies on maintaining a healthy soil biology and overall biodiversity. This may include providing a habitat for beneficial organisms, diverse rotations, using resistant varieties, intercrops, proper soil and nutrient monitoring and management, among others. When such preventative measures are insufficient to prevent or control pests, diseases and weeds, the addition of permitted PPPs would normally be the last resort. Such preventative techniques are difficult to account for in LCA and were not included in the EI and AG organic crop datasets, except crop rotations and intercrops to some extent in AG, where they allocate PPP and fertilizer manufacturing, emissions from PPP and fertilizer applications and diesel consumption among the crops in that sequence. Mechanical weeding was also accounted for in some of the AG crop datasets (Table B-1). The other preventative measures that require diverse ecological structures to increase biodiversity and habitats for beneficial organisms, which may also be referred to as ecosystem services, are difficult to account for in LCA as they are difficult to quantify and/or reach a consensus as to how to measure it. However, some studies aim to for example, estimate the vascular plant biodiversity in organic and conventional cropland in Europe (Knudsen et al., 2017; Koellner and Scholz, 2008; Mueller et al., 2014; Schryver and Goedkoop, 2010), which may be a good start.

2.4.1.2 PPP EMISSION MODELLING

The main critical aspect found to be relevant to environmental assessments of OA, was that the total PPP dose in compound form (e.g., $CuSO_4$) was often used as the emission output rather than the active ingredient (e.g., Cu ion).

Copper-based PPPs are one of the most widely used and most generously applied PPP in OA and CA, especially in fruit trees and grape vines (Agrios, 2005). Since OA cannot use other synthetic pesticides, organic farmers depend greatly on copper PPPs, and thus copper emissions are relevant and important. However, it seems there is confusion surrounding how to calculate emissions from copper-based PPPs; in AG, they used the mass of the compound (e.g., copper sulphate, copper oxide, etc.) as the on-field emission output, instead of using the mass of the active ingredient, Cu ion. This can consequently over-estimate toxicity results due to the higher, total mass used, especially when applied in solution or in acidic environments where the Cu is more likely to be a free ion. For example, the total input dose used in the organic apple dataset in AG was 109.871 kg Cu/ha, which was equal to the total sum of output emissions (41.072 kg copper sulphate/ha and 68.799 kg copper oxychloride/ha), showing that the total dose was used instead of the amount of Cu active ingredient.

2.4.1.3 EFFECT OF PPP CRITICAL ASPECTS ON LCIA

Figure 10 shows the contribution of processes to the total impact for those organic crop datasets in EI and AG where relevant criticisms regarding PPP inputs were reflected in the life cycle impact assessment. This demonstrates how and to what degree the limitations discussed in the previous section affect LCA results, in order to show the importance these limitations have on current and future LCA studies.

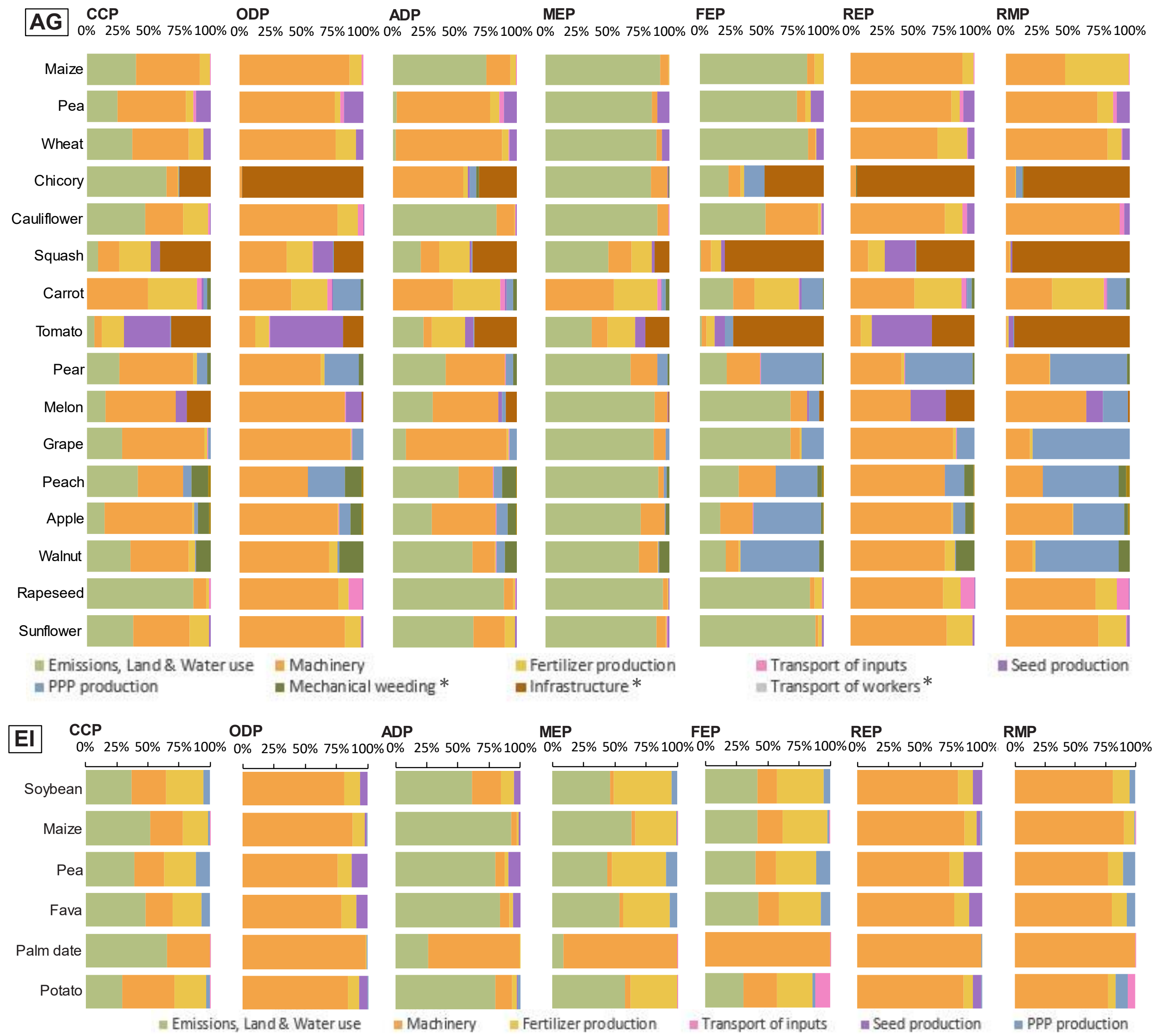


Figure 10. Contribution of relevant cultivation processes in organic crops from databases AGRIBALYSE® (AG) and ecoinvent (EI) to potential impact categories climate change (CCP), ozone depletion (ODP), acidification (ADP), marine (MEP) and freshwater (FEP) eutrophication, resource energy carrier use (REP), and resource mineral use (RMP). Machinery includes field work such as tillage, planting, harvesting, irrigation, PPP and fertilizer application, and the production of diesel, electricity and machinery required to carry out these operations. *Mechanical weeding was only present in walnut, pear, chicory, peach, apple, wine grape and carrot. *Infrastructure was only present in chicory, squash, tomato and melon. *Transport of workers was only present in wine grape, apple and peach.

Perennial fruit and nut production in AG, used more PPPs than the other crops, which was clearly reflected in the results where PPP production notably contributed between 4 – 30% to ozone depletion (ODP), 6 – 11% to acidification (ADP), 7 – 64% to freshwater eutrophication (FEP), 7 – 55% to resource energy carrier use (REP) and 22 – 78% to resource mineral use (RMP) (Figure 10). These PPPs constituted copper and sulfur fungicides, kaolin, pesticide unspecified proxy for Spinetoram, petrol proxy for mineral oil, and electricity proxy for *Bacillus thuringensis*. Of these values, copper-related PPP production was the main contributor to FEP due to upstream phosphate emissions and RMP due to depletion of resources, whereas sulfur production was the main contributor to REP, demonstrating the energy-intensiveness of its production (Figure B-1). Therefore, it is important that adequate copper datasets are chosen when carrying out an LCA of crops that use copper, and it is pertinent that the data quality of these copper datasets are improved or are discussed in the LCA. However, this is based on the assumption that the copper used in the EI database is of virgin origin, whereas in reality 40 – 50% of all pre-manufactured copper is sourced from recycled copper scrap (Davenport et al., 2002). However, in regards to the characterization of the impacts due to these copper compound emissions, the characterization method EF 3.0 (used in this study) and even another commonly used method ReCiPe 2016 (Huijbregts et al., 2017) do not have toxicity CFs for these compounds or they are not properly accounted for in SimaPro. Thus, the toxicity impacts of copper oxide, copper sulfate and copper oxychloride emissions would not be accounted for, which is why toxicity impact categories were not included in this study. Therefore, if EF 3.0 or ReCiPe is the characterization method of choice, it is recommended to use copper (CAS Number 007440-50-8) as the output emission, since these impact methods assign the CFs for the oxidized form of copper (Cu(II)) to the metallic form. Therefore, this change is important for crops that use large amounts of copper fungicides, potentially affecting categories that are affected by copper emissions to soil, i.e., freshwater ecotoxicity and human toxicity non-cancer. In summary, it is recommended to i) use the amount of active ingredient (e.g., Cu ion) as the output emission in crop LCIs, instead of the compound (e.g., copper sulphate), if applicable, and ii) use copper (CAS Number 007440-50-8) as the output emission instead of the compound (e.g., copper sulphate).

Of the AG crops that inventoried pesticide unspecified as a proxy for Spinetoram (Table B-1), peach had the highest amount of pesticide unspecified applied with 51.48 kg/ha followed by carrot with 13 kg/ha (other crops were in the range of 0.00702 kg – 7.6 kg/ha). Looking at these two crops, it is evident that these high amounts of pesticide unspecified can sway the results away from copper and sulfur impacts, causing high contributions in FEP (15%) and REP (13%) (Figure B-1). Since the amount of "pesticide unspecified" used in peach production is relatively smaller compared to copper (1.3x lower) or sulfur inputs (36x lower), these results indicate that even a small amount of this PPP can greatly influence LCA results.

The impact of mechanical weeding was estimated apart from machinery processes, in order to separately account for other methods of weed removal that may be used in OA instead of herbicides. Mechanical weeding was used in the AG perennial crops datasets (wine grape, apple, peach, pear, walnut), and carrots. Since mechanical weeding consisted of the use of a tractor and its implements, it was found to potentially contribute 3 – 15% to CCP, 2 – 20 % to ODP, 3 – 14% to ADP, 3 – 15% to MEP, 2 – 15% to REP, and 2 – 9% to RMP (Figure 10). Therefore, it is important to separately account for this when carrying out an OA LCA.

2.4.2 CRITICAL ANALYSIS OF FERTILIZERS USED IN ORGANIC CROP DATASETS

2.4.2.1 BACKGROUND FERTILIZER MANUFACTURING DATASETS

Organic fertilizers are essential in OA, due to the prohibition of mineral fertilizers. Thus, after analyzing the OA datasets it was found that the main LCI modelling issue regarding the manufacturing of organic fertilizers and amendments was the exclusion of treatment and storage processes of the fertilizers (e.g., composting, anaerobic digestion) and the use of mineral fertilizer proxies (Table 6). This was likely due to the lack of usage statistics for organic fertilizer for the treatment to be included. For example, in AG and in EI, most crops had “organic farm or manure empty processes” to represent animal manure- or slurry-based fertilizers thus they were assumed to carry zero environmental burden from the animal production system. However, further valorization treatments of processes were not included in most of the crop datasets, with the exception of sunflower, rapeseed, tomato, squash and chicory. Given the dependence of OA on organic fertilizers and the growing number of organic farms and market for organic products in Europe (Eurostat, 2022), organic residue treatment may shift from mere treatment to economic valorization and entry into the market, showing the importance to include this in future LCAs.

With respect to the use of mineral fertilizers proxies in AG, average French P_2O5 or K_2O mineral fertilizers were inventoried in organic grape, carrot, sunflower and pea, in addition to average European N mineral fertilizers in grape (Table B-1), which are not authorized in OA. Only crude or rock phosphate and organic fertilizers are permitted (all authorized fertilizers for organic production are listed in Table 1 (European Commission, 2008a).

In regards to the data quality for those fertilizers with available manufacturing datasets (Table 6), green manure, compost, all three average mineral fertilizers of N, P_2O_5 and K_2O and potassium chloride had good W-DQRs between 2 – 3. Poultry manure had fair W-DQR between 3 – 4, due to poor completeness and temporal correlation ratings across all inputs and outputs. EI stated that this dataset is a rough estimation extrapolated from literature sources, and that it is recommended to update this dataset as soon as possible. Horn meal also had a fair rating due to poor temporal correlation across all inputs and outputs, especially electricity and heat processes, possibly due to the extrapolation of data from 1993 to 2019.

Table 6. List of fertilizers and amendments used in organic crops from EI and AG databases and the ORG+ project, and corresponding availability of manufacturing datasets and data quality information.

Fertilizer	Manufacturing/treatment dataset available? – Database?	Average W-DQR weighted by impact contribution to total
Liquid and solid farmyard manure (empty process, only accounted for in terms of direct field emissions)	N/A	N/A
Digestate	Yes - AG v3.0	2.60[a]
Composted farmyard manure with and without substrates	Yes - AG v3.0	2.60[a]
Green manure	Yes – EI	2.04
Horn meal	Yes – EI	3.20
Compost (type not specified)	Yes – EI and AG	2.17
Average P_2O_5 mineral fertilizer	Yes – EI	2.32 (based on Phosphate fertilizer, as P_2O_5, monoammonium phosphate production as it was the input with the highest proportion) 2.36 (based on Phosphate fertilizer, as P_2O_5 triple superphosphate production)
Average K_2O mineral fertilizer	Yes – EI	2.81 (based on Potassium chloride production, as K_2O as it was the input with the highest proportion)
Average N mineral fertilizer	Yes – EI	2.23 (based on ammonium nitrate production, as N as it was the input with the highest proportion)
Poultry manure	Yes – EI	3.07
Potassium chloride	Yes – EI	2.81
Magnesium oxide	Yes – EI	4.04
Potassium sulphate	Yes – EI	2.33
Commercial liquid fertilizer (Calcium (7) and magnesium)	No	N/A
Commercial pelletized cow manure	No	N/A
Commercial liquid vegetable-based fertilizer	No	N/A

[a]This is not a weighted DQR, this could not be weighted due to unavailable DQR for each individual input for that dataset, thus, the average of the quality assessments given in (Avadí et al. 2020, Table 4, from which these LCIs were derived) are shown here.

2.4.2.2 FERTILIZER EMISSION MODELLING

Fertilizer application emissions can affect acidification, eutrophication, climate change and toxicity potential, and are calculated first and foremost as a function of nutrient and heavy metal content (e.g., 0.55 TAN in dairy cattle manure applied, European Commission, 2017), as well as other factors such as climate and application technology. Thus, we highlight three main limitations that can greatly influence impacts in regards to fertilizer application emission modelling in not only OA but also any agricultural production system that uses organic fertilizers:

(1) No differentiation is made between the nutrient content for manure derived from OA and CA systems.

(2) Fertilizer emission models such as those used by AG and EI (and hence used by the European Commission (2017)) are too simple for accounting nutrient balance and heavy metal emissions from organic (and conventional) fertilizer application.

(3) Use of averages for nutrient content composition for organic fertilizers can yield unrepresentative emissions due to high variability

The average nutrient composition of organic fertilizers used in EI and AG were based on manure from all types of agricultural systems, such as from CA and OA. However, due to the higher number of conventionally managed farms in Europe compared to OA, the nutrient content is often based only on manure from CA. This is an issue for two main reasons, 1) use of manure from factory farming as fertilizer is prohibited under EU OA regulations, 2) N-content in manure from CA can be higher than OA due to higher protein content in the feed. The latter is rarely ever considered in LCA inventories and may be an important explanation for unaccounted N surplus in LCAs of organic products, especially for animal products (Meier et al., 2015). Thus, Meier et al. (2015) state that ammonia emission models should be adapted to different farming systems, such as taking the diet-related N-flows into account, to allow more accurate estimates for acidification, terrestrial eutrophication and climate change potential, especially within comparative LCAs of animal products.

In respect to the second limitation, the fertilizer application emission modelling in AG and EI did not take into consideration the application method by which fertilizers, whether organic or not, are applied when estimating ammonia emissions. This is extremely applicable to OA since some organic fertilizers emit more ammonia than mineral fertilizers (e.g., default air emission factor for organic fertilizer is 0.24 kg NH_3/kg N applied and 0.12 kg NH_3/kg N applied for synthetic fertilizers, European Commission, 2017). Moreover, misrepresenting NH_3 emissions can also affect NO_x emissions generated through nitrification and N_2O emissions through denitrification. AG state that lack of fertilizer application data in France made it impossible to create correction factors for ammonia. In the estimations for EI data, it was assumed that no additional measures were taken to reduce ammonia emissions. AG also explain that their nitrate emissions were estimated using the COMIFER-Tailleur model (Tailleur et al., 2012), which does not take into account the dose of nitrogen supplied, and the time at which it made the contribution. Additionally, AG and EI used the SALCA-P model which does not take into account the fact that P balances are not always balanced, with exports being stronger than inputs. For example, AG state that this is a limitation in their study since successions with alfalfa export a lot of P, thus without adapted agricultural practices, P stocks in soil are likely to decrease (Nitschelm et al., 2020).

Heavy metal (HM) contaminants can be found in both organic and mineral fertilizers, however, higher levels have been found in organic fertilizers and/or are more readily available, although uptake may be lower due to organic matter content in the fertilizers (Ugulu et al., 2021; Zaccone et al., 2010). Therefore, HM emission modelling is a very critical aspect to consider. For both AG and EI, the SALCA-heavy metal soil emission methodology (Prasuhn, 2006) was applied; a balance between heavy metals (HM) inputs into soil (seeds, fertilizers, pesticides and deposition) and outputs from the soil (exported biomass, leaching and erosion) was made, resulting in either positive or negative emissions. One major difference between AG and EI fertilizer emissions modelling is that AG includes the effects of crop rotation on emissions, but these have resulted in negative net HM emissions. AG state that a negative emission means a net export of HM to water bodies or to the harvested product such as food, feed or straw through uptake or residue. However, the uptake values were based on average HM contents of specific crops and specific fertilizer types for France or Switzerland. AG further stated that trace HM leached to aquifers is strongly linked to the geology of the soil, so the values they used from Switzerland (the average amount of HM leached per ha per year) should be used with care when applying it to other countries. Furthermore, AG adds a disclaimer that considering the uncertainties of these parameters, a negative balance should not be interpreted as complete export of HMs from the field, but mainly as a result of uncertainty in input and output data. Therefore, LCA practitioners must bear this in mind when interpreting emission results that use balancing methods like SALCA-HM emissions modelling in the LCI, and it is recommended to report results with and without negative HM emissions (i.e., zero emissions if the value is negative).

In regards to the third limitation, information regarding nutrient content in organic fertilizers is often unavailable or reported only as the total amount of fertilizer applied. Thus, proxies or national weighted averages based on market data are often used, but may not be representative of the region or fertilizer type under investigation, and could lead to under- or over-estimation of emissions. However, therein lies the limitation, it is difficult to create proxies for organic fertilizers due to the large number of fertilizer types available and high variability in nutrient content among them. For example, from the data gathered for the ORG+ reference scenarios, pelletized fertilizers, or commercial liquid vegetable fertilizers were used on-field, but no representative nutrient contents nor emission fractions could be found for these fertilizers. Thus, if emissions are to be estimated, proxies would need to be used which can increase uncertainty of results. For instance, pelletized fertilizer usually has lower emission rates than solid manure or digestate (Pampuro et al., 2018).

The variability of nitrogen content among organic fertilizers is quite high depending on the database or source chosen (Figure 11). Koch and Salou (2016) for AG had the lowest variability and Flisch et al. (2009) for EI had the highest variability, illustrated by the size of the boxplots in Figure 11. If an average is taken (e.g. 11 kg N/ton in Flisch et al., 2009), there is a 50% chance that the actual nutrient content of a specific fertilizer may be more than double the average (e.g. >22 kg N/ton). Another important point that can be derived from Figure 11 is that the “outliers” all represent nutrient values for poultry manure, hence showing that this type of fertilizer is statistically different from the rest.

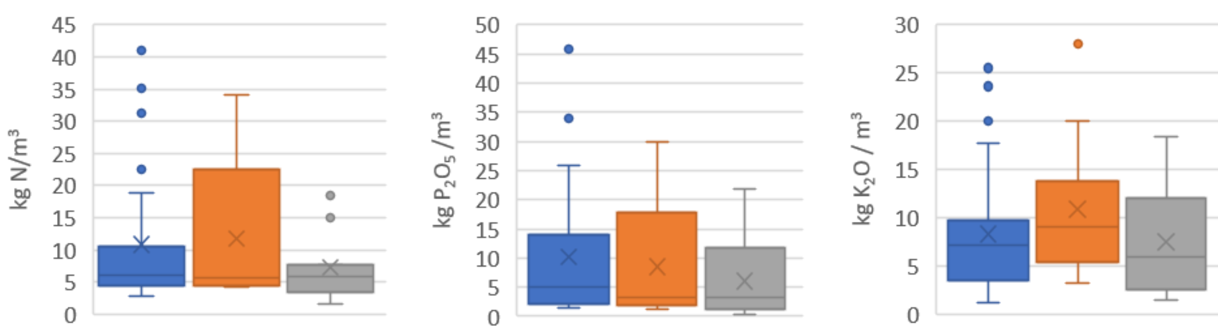


Figure 11 Comparison of nutrient content (kg N, P2O5 and K2O per m3 or ton) in different types of organic fertilizer derived from animal and sewage waste from Catalonia, Spain (Sío et al., 2013) in blue, ecoinvent (Flisch et al., 2009) in orange, AGRIBALYSE® (Koch and Salou, 2016) in grey. Each boxplot shows the median of all values (line through the box), mean (cross), flanked by the first (bottom) and the third (top) quartiles (limits of the box) and first (bottom) and ninth (top) deciles (whiskers), outliers are plotted as individual points. This graph is based on data from Table B-2.

2.4.2.3 ALLOCATION OF MANURE

One other important point regarding inventory modelling of organic fertilizers is how to allocate organic residues (e.g., manure) that are exported off-farm. Since this study also aims to guide LCA practitioners in applying LCA to OA products, we will discuss how current literature and databases deal with allocation, so that future LCA studies can allocate with more consistency. The allocation of manure is one aspect that can be part of either the animal or crop production system, and because it is at the interface of both, it is important to have a clear and consistent approach as to where the manure should be allocated. This is especially relevant to OA due to the strict use of organic fertilizers, but also relevant to conventional agriculture that may use a mixture of organic and mineral fertilizers. This is a crucial aspect that must be properly and consistently assessed seeing as manure management processes can represent high contributions to impact categories such as climate change, acidification, particulate matter and eutrophication, due to methane and nitrogen-related emissions.

The Livestock Environmental Assessment and Performance (LEAP) Partnership by the Food and Agriculture Organization of the United Nations (FAO 2016; 2018) offers clear and robust guidance for the allocation of manure. This Partnership is a multi-stakeholder global initiative that seeks to improve the environmental sustainability of the livestock sector through harmonized methods, metrics, and data, particularly guiding the use of LCA in livestock systems. The LEAP Partnership recommends to first classify the organic residue as either a co-product (of the producing system), a residual or a waste. This allows the system to be separated into two areas, where all post-farm emissions from manure use are assigned to that use, while all on-farm management is assigned to the main product(s) from the farm (e.g., milk, manure, live animals, draught power).

Table 7 summarizes how to classify an organic residue as a co-product, residual or waste, where and how to allocate any further treatments, and any associated criticisms. The LEAP guidelines state that the application of consequential modelling by system expansion and substitution is not supported by the guidelines so that greater harmonization among the different guidelines may be achieved. The allocation methods described therein are to be used for attributional LCAs but system expansion may be used in the context of including expanded functionality, though it is a conventional approach. Seeing as the LCI datasets used in the current study were created using an attributional approach, i.e., an average technology mix as opposed to the consequential marginal technology approach, the attributional approach is discussed here for greater consistency.

Manure can be classified as a co-product if it can be sold as a source of revenue for the farmer, similar to the other outputs of the farm (e.g., milk, live animals, wool). Since there is more than one product that exits the animal farm, a biophysical or economic allocation method can be used. However, it is important that the same allocation method is used throughout the supply chain for consistency. Please refer to (Food and Agriculture Organization, 2016) for specific steps on how to carry out the allocation. Manure is classified as a waste when is has no value nor is reused, such as in the following two situations, i) deposition in a landfill, incineration or treatment facility, or ii) when applied to the field in excess of crop requirements, and emissions from deposition and field application are allocated to the animal product(s). If a LCA on animal production is being carried out, it is pertinent that the most accurate dataset for disposal method is chosen or modified to suit the actual situation. For accurately estimating how much of the manure is in excess, the LEAP guidelines provide the steps required (Food and Agriculture Organization, 2016). Finally, a manure is considered to be residual if the manure is of no value to the farmer, but exported off-farm for value-added processes or application to crop fields within crop nutrient requirements. This follows the “cut-off” system separation, where the manure does not contribute any burdens to the animal product(s) nor to the off-farm processes, they come “burden-free” from the animal system to subsequent uses. Therefore, any burdens associated with off-farm processes such as value-added processes (e.g., anaerobic digestion, composting to make a fertilizer) are allocated to the system consuming it (e.g., crop system consuming it as fertilizer). It is essential that the value-added processes are not double-counted in both the animal system and crop system when carrying out a livestock LCA.

Table 7. Summary of LEAP guidelines on allocation procedures of manure exported off-farm (Food and Agriculture Organization, 2016). Additionally, these guidelines have a decision tree to aid the decision-making process.

	Definition	Method for allocation	Critical aspects to consider
Co-product	It is a coproduct when manure is a valuable output of the farm, and if the system of manure production cannot be separated from the animal production system. The full animal supply chain to the farm gate is shared between all the co-products (e.g., milk, live animal, manure).	1) Biophysical: based on the energy required for digestion to utilize nutrients and create manure. 2) Economic: based on a value:quantity ratio. Used if energy content of feed is unknown and if function of product is not for energy (e.g., fertilizer instead).	Recommended to use the same allocation method throughout the supply chain, if inconsistencies occur, practitioners must transparently report possible impacts of this on the results.
Waste	Classified as a waste in two situations:	1) All emissions associated with disposal technique are assigned to animal product(s).	Choosing the most suitable dataset for disposal techniques
	1) When disposed in a landfill, incineration without energy recovery, or sent to a treatment facility 2) When applied in excess of crop nutrient requirements	2) Fraction that is in excess of crop requirements are classified as waste, thus field application emissions or disposal are assigned to the animal product(s). Fraction of manure applied that meet crop needs are defined as residual.	Accurately estimating how much of the manure is in excess, guidance is given in LEAP (Food and Agriculture Organization, 2016).
Residual	When manure is of no value to the animal farmer and is exported in the condition in which they were created. This classification is equivalent to the “cut-off” system separation, where the manure comes “burden-free” from the animal system as the boundary was cut-off after its transport off-farm.	Value-added processes and associated emissions as well as field application emissions are assigned to the system consuming it, e.g., crop system consuming it as a composted fertilizer.	Must ensure no double counting of manure management in both the animal and feed systems if carrying out a livestock LCA.

In both EI and AG crop datasets, farmyard manure was classified as residual, thus came "burden-free" from the animal production system. However, only the field application emissions were accounted for in the crop datasets and no value-added processes were included. It was not clear in the EI and AG documentation if this was because the manure was applied raw without further value-added treatment, but since no extra value-added processes were included in the LCI it can be assumed that raw application was used. In the European Regulations on organic food and labelling (European Commission, 2008a), the composting or treatment of raw manure before application on field is preferable to reduce contaminants, pathogens and aid decomposition. Thus, crop datasets that include value-added processes for manure would be useful or should be added to the LCI at the practitioner's discretion.

In the potato and legume EI datasets, green manure was treated as a residual, therefore, the production of the green manure in the rotation was allocated to the main crop under study (potato and legume). EI also treated horn meal, dried poultry manure and compost as residuals, where methodological documents for EI (Nemecek and Kägi, 2007) state that the treatment and recycling of organic by-products, and transport to and including regional storage are normally included in the datasets of these types of organic fertilizers, but under greater inspection of the LCIs, only transport to the farm was inventoried in the cut-off processes of these datasets.

Another novel approach to manage the allocation of burdens associated with recycling of organic residues is the Circular Footprint Formula (CFF). It is an end-of-life modelling formula that accounts for benefits and burdens for recycling, energy recovery and the use of secondary materials, from the European Commission's Product Environmental Footprint Category Rules (European Commission, 2017). This could be used if the practitioner would like to comply with the PEFCR, especially for European products, but currently, there is no adapted CFF for the use of by-products for organic fertilizer use.

2.4.2.4 EFFECT OF FERTILIZER CRITICAL ASPECTS ON LCIA

The fertilizer production contributions in Figure 10 includes both mineral and organic fertilizer manufacturing datasets, where applicable (see Table B-1 for further information). Focusing on the mineral fertilizer manufacturing impacts, the sunflower, maize, winter rapeseed and pea datasets in AG all used average mineral fertilizers K_2O and P_2O_5, which the sum of the two contributions to the total impact resulted in combined contributions between 2 – 8% to CCP, 4 – 10% to ODP, 1 – 8% to ADP, 2 – 7% to FEP, 2 – 15% to REP, 10 – 51% to RMP, and most notably 70 – 107% to freshwater ecotoxicity (FEx), except for maize (Table B-4). The freshwater ecotoxicity impacts were due to the upstream emissions of sulfur to river water from the production of potassium chloride, a precursor of K_2O. Carrot in AG inventoried ~10x more average K_2O and P_2O_5 mineral fertilizer than the other relevant crops, thus had higher contributions to CCP (11%), ADP (10%), FEP (26%), and RMP (11%) (Table B-5), demonstrating the influence mineral fertilizer production proxies can have across these categories.

In regards to the fertilizers permitted in OA and used in AG, horn meal, lime, quicklime, compost, potassium chloride, wheat straw, magnesium oxide, industrial biowaste compost, and inorganic chemical production (proxy for other organic fertilizers), had upstream burdens allocated to it in terms of treatment, transport and infrastructure, where applicable. Horn meal was used in soft wheat, sunflower grains, apple, walnut and pear crops, but looking only at soft wheat where horn meal was the only input besides machinery, transport and seeds, it can be clearly seen that the most relevant categories for horn meal were CCP, ODP, FEx, REP and RMP, with contributions of 11.64%, 15.94%, 33.53%, 23.61%, 11.26%, respectively (Table B-4). The other four crops had many other fertilizers and/or PPP inputs, thus the impacts for horn meal were lower as the overall impacts were more spread among them, however, the same pattern of the relevant categories for these crops can also be seen (Table B-4 and Table B-6). Since these categories were the most affected, it shows the energy intensiveness of horn meal processing.

Quicklime was used in the cauliflower, chicory root production and tomato datasets, but similar to horn meal in soft wheat production, quicklime was the only input in the cauliflower dataset besides machinery, transport and seeds, hence showing high contributions to CCP (21%), ODP (17%), FEx (15%), REP (14%) (Table B-5), compared to chicory and tomato (contributions between 0.007% - 3% across all categories, Table B-6).

Average compost, from green waste, biowaste, sludge, manure, slurry, was used in sunflower, squash and tomato AG datasets, where the most relevant categories were CCP, ODP, ADP, MEP, and REP with contributions between 10 – 25%, 6 – 19%, 6 – 25%, 0.83 – 21% (mean 12.54%), and 9 – 12%, respectively

Table B-4, Table B-5, Table B-6). This shows the importance treatment processes may contribute to the life cycle assessment of crops.

Potassium chloride was used as K2O fertilizer in carrot, tomato and apple AG datasets, and had low contributions across all categories between 0.03 – 6%, except FEx with 34% in carrot, 17% in tomato and 2% in apple (Table B-5, Table B-6).

Biowaste industrial compost and inorganic chemical organic fertilizer proxy had low contributions across all categories in the relevant crop datasets in AG, with values between 0.05 – 6%, showing its possible low importance overall (Table B-5, Table B-6).

Magnesium oxide and lime had very low contributions across all categories in the relevant crop datasets in AG, with values between 0.001% - 0.58% (Table B-6).

Wheat straw was used as mulch for carrot production in large quantities (20,000 kg/ha), and had high contributions between 24 – 32% to CCP, ODP, ADP, MEP, REP, RMP (Table B-5), as this flow includes baling and transport from the cultivating area, showing its possible high importance overall.

The only organic fertilizers with upstream production burdens in the EI database were green manure in soybean, fava bean, pea, potato, maize in EI, where it included all activities related to its cultivation. Green manure had similar contributions in all related crops, with high average contributions to CCP (23%), FEP (30%), MEP (39%) and RMP (10%) (Figure 10). Also, poultry manure in palm cultivation included upstream production burdens, but only the transport to the farm, and as expected, the transport had between 0 – 1% contributions across all categories.

2.5 DISCUSSION

The discussion was divided into two topics, spread over four sections, the first topic and section explains general criticisms about the EI and AG database (Section 2.5.1), and the second topic includes recommendations for improving organic crop LCIs, with respect to fertilizer inventories (Section 2.5.3) and PPP inventories (Section 2.5.1). Finally, a summary of the main recommendations is given in Section 2.5.4. The purpose of these recommendations is to provide proxies, guidance, as well as oriented prioritization of further research.

2.5.1 GENERAL ANALYSIS OF THE EI AND AG DATABASES

The organic datasets made by AG, were based on "a typical case" from one or a few case farms, as well as expert opinion, and thus do not represent average data for France, as stated in the methodological document by Nitschelm et al. (2020). Due to this, organic datasets cannot be used in the same way as the data in CA in the AG database, thus, cannot be used to make comparisons between OA and CA, without explicitly highlighting the limits of such a comparison. However, they can be used to: "…characterize part of the diversity of organic farming systems and some of their environmental impacts; identify areas for improvement and carry out eco-design work; perform sensitivity analyses; or even make system choices in a given context" (Nitschelm et al., 2020, Pg. 8). The EI organic crop datasets were based on statistics, pilot networks, documents from extension services, information provided by retailers and expert knowledge, and represent regional data, though only for cases in lowland Switzerland, thus, could be used in comparative contexts. In general, we found that the inventory for AG included more information that was readily available in the LCI itself. Particularly useful was the inclusion of emissions even for those inputs that did not have manufacturing LCIs (e.g., PPPs like biological control agents), as well as comments on what that input was used for (e.g., plant protection), allowing for more transparency. AG also provides specific methodological documents on OA (Grasselly et al., 2017), whereas EI provides only general methodology guidelines, none specific to OA.

2.5.2 PLANT PROTECTION PRODUCT INVENTORY IMPROVEMENTS

In regards to the lack of manufacturing LCIs for many organic-authorized PPPs (Section 2.4.1.1), improvements were suggested in the form of new LCIs for Spinosad and *Bacillus subtilis* (Table B-8, Table B-9), using the CeBER Bioprocess Modeler (Harding and Harrison, 2016a, 2016b) for building LCIs for microbial-derived products. The energy and carbon source requirements for their production (major hotspots in production, Harding, 2008) and available proxies are summarized in

. The authors state that the data was drawn from various industrial norms and academic sources, as well as stoichiometrically calculated values, and hence can be the source of inventory variations from other literature studies. The model is quite robust and complete in generating LCIs for microbial processes, as seen upon testing and comparing to literature studies (Harding, 2008), but the authors state that if LCA comparison results are within 5 % of each other, they may not be significantly different owing to uncertainty in the inputs and LCA inventory datasets. To generate the LCI for *Bacillus subtilis,* the CeBER model already contained an LCI for *B. subtilis*, thus default values were cross-referenced and updated, if necessary, with literature data (Korsten and Cook, 1996; Posada-Uribe et al., 2015; Rowe and Margaritis, 2004). The same was done for Spinosad using the literature data in Table 8.

These two new LCIs were judged to have an average DQR of 1.8 (derived from pedigree matrix values of 1,1,2,4,1, reliability, completeness, temporal correlation, geographical correlation, further technological correlation, respectively).

A new LCI was also created for Chitosan, a natural sugar-based pesticide and plant growth enhancer derived from the shells of crustaceans, using industrial production data from Pighinelli (2019) and Said Al Hoqani et al. (2020), where summarized data can be found in Table 8 and detailed data in Table B-10. Table 8 also provides information on PPPs that already have LCI datasets, and where further research is still needed.

This data could be a first step towards making a more suitable proxy for organic-authorized PPPs in Europe, rather than the use of “pesticide unspecified” default datasets, as done in AGRIBALYSE®. This proxy could be created by calculating a weighted average of all organic-authorized PPPs used in Europe. However, further research is needed on market data and new manufacturing datasets for other missing and prevalent PPPs (Table 8).

Table 8. Prevalent plant protection products (PPPs) used in organic agriculture (OA) in Europe in alphabetical order and their subsequent manufacturing datasets or suggested inputs (electricity and/or other significantly impacting inputs) that can be used as a proxy.

Prevalent PPPs used in OA	Suggested LCI for manufacturing of PPP	Reference
Bacillus subtilis	Electricity: 1.41 MJ/kg *B. subtilis* Glucose: 0.064 g/kg *B. subtilis* (These are the most impacting inputs, refer to Table B-9 for full LCI)	Model: (Harding and Harrison, 2016a, 2016b) Data used for model: (Korsten and Cook, 1996; Posada-Uribe et al., 2015; Rowe and Margaritis, 2004)
Bacillus thuringiensis	Proxy: *B. subtilis* data from above	
Bordeaux mixture	ecoinvent Bordeaux mixture	(Wernet et al., 2016)
Chitosan	Electricity: 5957.6 kWh/kg chitosan (This is the most impacting input, refer to Table B-10 for full LCI)	(Pighinelli, 2019; Said Al Hoqani et al., 2020)
Copper oxide	ecoinvent Copper oxide	(Wernet et al., 2016)
Copper oxychloride	Proxy: ecoinvent Copper oxide	(Wernet et al., 2016)
Copper sulphate	ecoinvent Copper sulphate	(Wernet et al., 2016)
Essential plant oils (e.g., cinnamon)	AGRIBALYSE® 3.0	(AGRIBALYSE, 2020)
Kaolin	ecoinvent Kaolin	(Wernet et al., 2016)
Mineral oil	ecoinvent Paraffin oil. Other: kerosene oil has similar production processes and has been used in LCAs (Niccolo et al., 2018). For output emission proxy: Petrol, low sulfur production, used by AG for output"	(Wernet et al., 2016)
Neem seed oil	Diesel: 17.3 L/ha/y Electricity: 5.56 MJ/kg neem seed	(Kumar et al., 2021)
***Nesidiocoris tenuis* (predatory insect)**	Needs further research	
Potassium soap	ecoinvent potassium hydroxide (KOH) + sunflower/vegetable oil (ratio of 100grams KOH:50mL oil)	(Wernet et al., 2016)
Pyrethrin	Proxy: ecoinvent pyrethroid-compound production	(Wernet et al., 2016)
***Reynoutria sachalinensis* (giant knotweed) extract**	Needs further research	
Spinosad	Electricity: 10.49 MJ/kg Spinosad Glucose: 0.055 g/kg Spinosad (These are the most impacting inputs, refer to Table B-8 for full LCI)	Model: (Harding and Harrison, 2016a, 2016b) Data used for model: (Lu et al., 2017; Xue et al., 2013)

With respect to accounting for the correct amount of copper active ingredient emission to the ecosphere (Section 2.4.1.2 and Section 2.4.1.3 for effects on LCA results), stoichiometry can be used to calculate the copper active ingredient mass from the dose of the copper compound. Table 9 shows the percent of copper in each relevant compound used as fungicides in agriculture. To calculate the amount of copper a.i. emitted, multiply the percent Cu by the dose of copper compound applied. For the apple example (Section 2.4.1.2), 41.072 kg copper sulphate/ha and 68.799 kg copper oxychloride/ha were applied on-field. To calculate the amount of copper a.i., multiply the dose by their corresponding % Cu in Table 9 (39.813% and 59.509%, respectively), to get 16.351 kg Cu and 40.941 kg Cu, respectively. Hence, by accurately accounting for copper emissions, freshwater toxicity results may be reduced since the amount of copper emitted to the soil has decreased.

Table 9. Percent of copper, Cu, (w/w) in each type of compound using stoichiometric ratios.

Copper compound	Percent (%) Cu
Copper (II) sulphate	39.813
Copper (II) oxide	79.887
Copper oxychloride	59.509
Copper (II) gluconate	14.003

2.5.3 FERTILIZER INVENTORY IMPROVEMENTS

In order to improve organic fertilizer LCI proxies (Section 2.4.2.1), organic fertilizer LCIs should be used instead of mineral fertilizer proxies, such as those from Avadí et al. (2020) which were based on secondary data in France, follow a gate-to-gate scope, and resulted in an important step forward. A summary of default values for the average electricity, heat and water needed for the treatment of organic residues under different treatment processes are shown in Table 10 derived from Avadí et al. (2020) and EI database. One may choose to adapt these processes to the country/region of the case study if data is available, or use them as a proxy (and transparently reporting this and the possible uncertainties). However, adaptation is prioritized over the use of proxies, since variability in nutrient content and emissions from the manufacturing process and field application is very high, as we have seen in Section 1.1.1.1 and further supported by these studies (Hayashi, Nagumo, and Domoto 2016; Montemayor et al. 2019; Avadí 2020). Thus, an example of a methodology to create more representative organic fertilizer LCIs include the methodology proposed by Avadí (2020) and Avadí et al. (2020) could be used, and is specific to organic fertilizers. Additionally, Koch and Salou (2016) outline a methodology for creating average mineral fertilizer datasets, and could be used for organic fertilizer if usage and nutrient statistics are available for each organic fertilizer in that region.

Table 10. Average of main resources needed for different organic treatments, data are reported per 1 kg fresh mass input (own elaboration based on Avadí et al. (2020) and ecoinvent database).

Treatment process	Output (kg)	Electricity (kWh)	Heat (MJ)	Water (kg)
Composting	4.40E-01	4.57E-03	3.99E-03	5.70E-03
Pelletizing	4.42E-04	4.87E-02	2.29E-01	
Digestate	9.30E-01	6.00E-03	1.28E-01	
Coffee processing (hulls, spent grounds)		6.60E-01	8.46E+00	8.57E+00
Olive processing		3.80E-01	0.00	3.28E+00
Pomace processing		3.00E-02	3.83E+00	0.00
Rendering of animal by-products		1.60E-01	4.37E+00	0.00

Additionally, Table B-3 provides suggestions regarding which LCI datasets from AG and EI could be used for each type of organic fertilizer or amendment permitted in OA in Europe. This work could be improved by the inclusion of other common commercial organic fertilizers and amendments such as, pelletized cow manure and liquid vegetable-based fertilizers (based on our ORG+ surveys, see Table 6). For instance, adapting the process for pelletizing poultry manure in EI to other types of pelletized animal manure, or use it as a proxy.

Additionally, a list of organic fertilizers and their nutrient content (Table B-2) adds variability to which the user can find suitable proxies or compare nutrient composition data for common organic fertilizers. If applying LCA on a case-by-case basis, instead of at national or high level, it is important that the practitioner knows at the very least, the type/source of fertilizer used (e.g., cattle manure, poultry manure, digestate), and use only the values for these types of fertilizers due to the high variability in nutrient content among organic fertilizers. This will ensure that accurate nutrient values and, consequently, accurate emissions are estimated. Nutrient compositions given in Avadí et al. (2020) can also be used as a proxy if the production and use of organic fertilizers in France is similar to the practitioner's case study.

In terms of advancing fertilizer application emission modelling (Section 1.1.1.1), many dynamic emissions models exist that may be suitable for organic fertilizers, such as Daisy (Hansen, 2000) and Animo (Rijtema and Kroes, 1991) which can be more dynamic than the SALCA model used by EI. These models have been reviewed in (Andrade et al., 2021) for their robustness and applicability in LCA, among other characteristics, and the practitioner can decide which is more suitable for their case. Indigo v3.0 (Bockstaller et al., 2022) is another model that looks at all types of emissions from fertilizers (N, P, K and HMs). It takes into account crop, climate and soil characteristics, mineral and organic fertilizer characteristics, and a wide range of organic fertilizers and their nutrient content at the global scale, making it more versatile than SALCA and the model used by AG, as they are only applicable in Switzerland and France. The integration of the Indigo v3.0 model into the modelling used in AG is planned for the future. In regards to ammonia emission modelling from fertilizer application, correction factors are available (Table B-7) and can be applied according to the weather conditions, fertilizer application machinery used (e.g. hoses, injection) and the time between fertilizer deposition and incorporation (Bittman et al., 2014; Brentrup et al., 2000; Søgaard et al., 2002). An example of its site-specific adaptation and use can be found in Montemayor et al. (2019). By changing the application technique of liquid slurry, the ratio of N-NH_3 emitted per total ammoniacal nitrogen (TAN) can range from 0% N-NH_3/kg TAN by injection to 48% N-NH_3/kg TAN emissions by broad sprayer, not incorporated, both in favourable weather conditions (Table B-7).

2.5.4 SUMMARY OF RECOMMENDATIONS FOR IMPROVEMENTS

Table 11. summarizes critical arguments and our recommendations for improving organic LCI datasets.

Table 11. Summary of critical analysis within LCA when assessing organic agriculture (OA) and the relevant recommendations and further research needed to advance in these aspects.

Aspect	Critical aspects	Rationale for criticality	Recommendation(s)
Fertilizer manufacturing data	Production of organic fertilizers (treatment and recycling) often not included in LCA of organic crops	Additional processing flows need to be taken into account for representativeness and for fair comparison with mineral fertilizer production.	Classify manure according to LEAP guidelines. Include upstream treatment and storage of organic residues in the life cycle of the product, using LCIs or methodology from Avadí et al. (2020), summarized in Table 10, and datasets suggested in Table B-3.
	Average mineral fertilizer production datasets were used in AGRIBALYSE® due to unavailable proxy for organic fertilizer production	Mineral fertilizers are prohibited in OA, and inclusion can cause high impacts in energy-related impact categories	Include only organic fertilizers to comply with OA regulations. Follow methodology from Avadí et al. (2020) or (Koch and Salou, 2016). If organic fertilizer is the same as those in AG (Avadí et al., 2020), they can be used as proxies.
Fertilizer emission modelling	No additional technical measures to reduce NH_3 emissions are considered when modelling NH_3 emissions.	Can under- or over-estimate NH_3 emissions and potential acidification and climate change if other more mitigating techniques are used. This can also affect NO_x (nitrification) and N_2O (denitrification) emissions.	Account for fertilizer application techniques in NH_3 emissions modelling, using correction fractions such as in (Table B-7, derived from (Bittman, S., Dedina, M., Howard C.M., Oenema, O., Sutton, 2014; Brentrup et al., 2000; Erica Montemayor et al., 2019; Søgaard et al., 2002). Regulations on how fertilizers are applied to the field should be made.
	Nutrient content for manure-based organic fertilizers is not adapted to OA.	Manure used as fertilizer from factory farming is prohibited in OA. N-content in conventional manure is higher than organically sourced manure due to high protein feed.	Take into account the diet-related N-flows in the organic animal farm to increase representativeness. Further research is needed on N-content of organic farm-derived manure (or general difference between organic and conventionally-derived manure).
	Negative heavy metal (HM) emissions	Swiss Agricultural LCA (SALCA) methodology was used in AGRIBALYSE® (AG) and EI, but in AG, this caused negative toxicity impacts, practitioners may interpret this as advantageous.	Negative HM emissions and toxicity scores should not be interpreted as complete export of HMs from the field, but rather as a result of uncertainty LCI data. Impact results should be reported separately from the total toxicity results. Further research needed in reducing uncertainty.

	Unbalanced P in inventory and poor accounting of nitrate emissions	SALCA-P model used for P emissions, but often results in unbalanced P in inventory. The COMIFER-Tailleur model used for NO_3^- emissions in AG, does not take into account dose and time of application.	Practitioners can use other more dynamic models that take these aspects into account: Indigo v3.0 (Bockstaller et al., 2022), Daisy (Hansen et al., 2000) and Animo (Rijtema and Kroes 1991), with meta-study by (Andrade et al., 2021).
Plant protection products (PPP)	"Pesticide unspecified" dataset was used as a proxy for unavailable PPP production datasets	This contains synthetic pesticides that are not authorized by OA regulations in Europe.	More research needed to create a regional "average OA-authorised PPP" dataset to replace "average pesticide, unspecified"
	Lack of PPP manufacturing datasets	Possible exclusion of relevant burdens from manufacturing.	New LCIs for a few PPPs have been created in the present study, or use suitable proxies for missing/prevalent OA-authorized PPPs given in **Table 8**.
	Rotenone inventoried as emission output in AGRIBALYSE®	Though rotenone was permitted in France during the reference period of the datasets that use it, it is now prohibited since 2011 in Europe.	Remove this emission output from the LCI if your reference period is after 2011 or if your crop does not use rotenone.
	The total compound dose (e.g., copper sulphate) is often used as the emission, rather than the active ingredient Cu	Could over-estimate toxicity results, as the mass of e.g., copper sulphate is 2.5x higher than the mass of copper within the compound	Use stoichiometry to calculate the amount of copper within the compound as the output emission (Table 9), especially if applied in solution or in acidic environments.

2.6 CONCLUSION

LCA presents some gaps in the adequate assessment of organic land management practices and their effects on agroecosystems, as there is a lack of background inventory datasets for the manufacturing of organic fertilizers and plant protection products and insufficient emission modelling. Therefore, it is important that the users of organic agricultural product datasets such as those from ecoinvent and AGRIBALYSE®, understand what limitations exist, as these can greatly affect the final LCA results. Practitioners should be fully aware of the limitations presented here, which are not clearly reported in the methodological documents of the databases. Users should account and adapt to regional differences including differences in organic agricultural policies such as prohibited practices and organic fertilizer composition. In the present study, the shortcomings of state-of-the-art OA LCI methodology were highlighted and suggestions on how to advance were given, such as:

- Creation of new LCIs for plant protection products used in OA
- Suggestions and examples on how to create more representative organic fertilizer LCIs
- Improve organic fertilizer and plant protection product emission modelling using recommended studies

The findings in the present chapter add much needed transparency regarding the limitations of available OA LCIs, offers guidance on how to make OA LCIs more representative, allow for more accurate comparisons between conventional and OA, and help practitioners to better adapt LCA methodology to OA systems. Further research is still needed in the creation of other plant protection product manufacturing datasets and regional organic fertilizers. LCA is an appropriate methodology to perform environmental assessment due to its comprehensive and system-based scope but it should be improved to better reflect organic agricultural practices.

CHAPTER 3

ANALYSIS OF TOP-DOWN AND BOTTOM-UP APPROACHES FOR MODELLING BIODIVERSITY LOSS IN AGRICULTURAL SYSTEMS USING LIFE CYCLE ASSESSMENT: A CASE STUDY OF LIVESTOCK PRODUCTION IN EUROPE

This chapter has been submitted as:

Montemayor, E., Bonmatí, A., Andón, M., Antón, A. Analysis of top-down and bottom-up approaches for modelling biodiversity loss in agricultural systems using life cycle assessment: a case study of livestock production in Europe. Submitted to the journal *Environmental Science and Technology*. Under Review.

Brief background:

Biodiversity has been found to be a chief distinguishing factor between organic and conventional agricultural systems, but research is still needed regarding the testing of currently recommended models for estimating biodiversity loss on farmland. This chapter is dedicated to researching some of the currently recommended LCIA biodiversity loss models, as well as one other model, to see which ones many be more suitable in specific contexts, for example, scale of data used to model biodiversity loss; top-down or bottom-up.

3.1 ABSTRACT

The need for better biodiversity loss modelling is becoming more and more pertinent due to increased pressures like land use change due to agriculture. Life cycle assessment (LCA) is an internationally standardized methodology to assess the environmental impacts of products across its entire life cycle. There are two general approaches that life cycle impact assessment (LCIA) models follow to estimate biodiversity loss due to land use pressures, top-down (prediction-based approach at ecoregion level), and bottom-up (field-measurement-based approach at local or regional level). This study aims to assess top-down models proposed by these international bodies, as well as models following a bottom-up approach by testing their performance as biodiversity indicators using lamb production case studies in Spain and Norway. It was found that the top-down models were sufficient for hotspot analysis in these cases since characterization factors (CFs) were available for all relevant ecoregions in the livestock supply chain. They were also able to identify plants, amphibians and reptiles as taxa that may be most at risk of extinction. It was also seen that fragmentation can have a large effect on mobile species like birds. However, top-down approaches could not statistically differentiate between land use types like cropland and pasture, nor minimal and light intensity classes. The CFs were mainly influenced by the area of the land use type rather than species or management characteristics, showing that it cannot be applied at more site-specific levels. The bottom-up models looked at potentially disappeared fraction (PDF) of plants due to more specific agricultural practices and land use types, based on real field measurements of species richness, which may make it more suitable for the foreground analysis. These models can potentially be applied to all spatial levels and can be parameterized with different land use and management types as long as there is data available. As the model currently stands, it cannot be used for background biodiversity loss modelling nor hotspot analysis as no CFs are available outside of Europe. It was also found that the semi-natural forest reference situation in the bottom-up model analyzed may not be suitable for comparisons with extensive pasture grazing, instead natural grasslands should be used as these promote biodiversity specific to this land use type. In general, a mixture of the two approaches could also be done; top-down approaches could be used for hotspot analysis, especially for background systems, and bottom-up for foreground systems. The choice between approaches or the combination of the two is driven by, 1) the goal and scope of your study, 2) the data available. If only hotspot, high-level or national assessments are needed or data is available only at this level, then top-down assessments would be suitable. If the goal is to study local biodiversity loss due to agricultural land use on a particular farm or area, then bottom-up approaches would be suitable. Therefore, if we are to transition towards sustainable agricultural practices,

management practices need to be focused on and captured better in LCIA methods for biodiversity loss due to land use pressures.

3.2 INTRODUCTION

In LCA, we find that there are two general approaches that life cycle impact assessment (LCIA) models follow to estimate biodiversity loss due to land use pressures, i) top-down approach, and ii) bottom-up approach. The difference between the two approaches is not only the scale in which the data was based upon, but also the way in which the modelling was approached, either based on predictions or field data. For example, this was previously defined in Curran et al. (2016) where they focus on the transformation of data for modelling; top-down approaches are process-driven where parametric functions were fitted to diversity data "…based on a predefined mechanistic relationship describing an observed process. The SAR is particularly common [SAR is the species area relationship in ecology demonstrating that as land area increases so does the number of species]." They describe bottom-up approaches as "…based on extracting statistical relationships from different types of empirical data at various scales (e.g., meta-analysis of comparative land use studies)." Curran et al. (2016) also explain that they are not mutually exclusive within a single model and are frequently used in combination. Thus, in order to define a clearer distinction between the two approaches, we classify approaches based mainly on the scale of data collection. We define top-down as a prediction-based approach where species extinction predictions were estimated by transforming regional species richness data using factors to reflect land use types, intensity levels, vulnerability of species, etc. In other words, biodiversity loss was estimated by extrapolating data from the "top" and applying it to lower scales (e.g., cropland within an ecoregion). We define and use the word "bottom-up" to reflect the fact that the characterization factors (CFs) used to estimate biodiversity loss are not predictions, but based on real species richness data from that particular farm or area, inherently accounting for geographical, managerial, and crop factors. The data starts at a local or "bottom" scale, which can then be extrapolated to higher levels.

Many land-use-based LCIA terrestrial biodiversity loss models exist which are listed in the review by Crenna et al. (2020), where almost all the recent models address the species aspect of compositional biodiversity, and only a few addresses the functional or ecosystem aspects. Only one model is recognized and recommended preliminarily by the European Commission's (EC) Environmental Footprint Technical Advisory Board (European Commission, 2022) and the LEAP-FAO Partnership (FAO, 2020), the model by

Chaudhary and Brooks (2018). Another model by Kuipers et al. (2021) is projected to be recommended by the technical advisory board in the near future (personal communication). These two models are endpoint methods which assess environmental impacts at the end of the cause-effect chain of an impact pathway which link the midpoint environmental impact to damages to areas of protection that are important to society (ecosystem quality, natural resources and human health), as opposed to midpoint methods which assess environmental impacts earlier in the cause-effect chain. These two models would be classified as top-down approaches according to not only our definition of top-down, but also Curran et al. (2016), seeing as they are based on predefined mechanistic relationships describing an observed process like SAR and data collection on species richness is done at higher regional scales (ecoregions).

In regards to models adopting a bottom-up approach as defined in Curran et al. (2016) and according to our classification, only one provides global midpoint CFs (Elshout et al., 2014), whereas the others focus on Germany and Switzerland (Koellner and Scholz, 2008, 2007) and the UK and Switzerland (Mueller et al., 2014). One main limitation across all the aforementioned bottom-up models is the fact that they are all based on meta-studies of species richness, gathering data from multiple studies with different species richness measurement techniques and sampling areas. Since 2016, one model by Knudsen et al. (2017) addressed this limitation by providing CFs based on species richness on cropland and pasture using *standardized measurement techniques* across six European countries in the Temperate broadleaf and mixed forests biome, making them inherently certain in terms of predicting species richness and applicable across a larger geographical area.

Both the EC Environmental Footprint Technical Advisory Board (European Commission, 2022) and the FAO-LEAP (FAO, 2020) call for case studies to test the performance of indicators. Therefore, this study aims to critically analyze the feasibility and applicability to livestock production systems of both top-down and bottom-up approaches by testing their performance as biodiversity indicators using case studies. The top-down models recommended by FAO-LEAP (FAO, 2020) and the EC Environmental Footprint Technical Advisory Board (European Commission, 2022), Chaudhary and Brooks (2018) and Kuipers et al. (2021), were analyzed as well as the bottom-up model Knudsen et al. (2017) since the CFs are more certain (in terms of their basis on standardized measurement techniques) and were based in the same biome as the case studies we used. We chose three different lamb production systems, one that grows nearly all its feed on-site in Norway, one that grows a small amount of feed on-site in Spain, and one that uses only compound feed in Spain. Livestock was chosen as a case study since it is one of the most important industries in terms of land use and economic gain in Europe (Greenpeace, 2019) and because it has a large value chain where top-down approaches may be useful.

Though many other critical analyses of LCIA biodiversity loss models exist (Crenna et al., 2020; Curran et al., 2016; FAO, 2020; Gabel et al., 2016; Gaudreault et al., 2020; Hayashi, 2020; Koellner et al., 2013; Kok et al., 2020; Lindqvist et al., 2016; Myllyviita et al., 2019; Souza et al., 2015; Teixeira et al., 2016; Winter et al., 2017), to the best of our knowledge, no other critical review has done the following: 1) reviewed these specific models recommended by experts (Chaudhary and Brooks, 2018; and Kuipers et al., 2021); 2) compared these to another model (Knudsen et al., 2017) in terms of scale of data collection, defined as top-down and bottom-up approaches, where Knudsen et al. (2017) would be defined as a bottom-up approach, and Chaudhary and Brooks (2018) and Kuipers et al. (2021) would be defined as a top-down approaches; 3) analyzed and tested all three models to a greater depth using livestock case studies in Europe. In doing this, important gaps came to light and suggestions for their application, as well as improvements and further research were provided. Specifically, no previous review has analyzed the model by Kuipers et al. (2021) due to its recent publication last year. Some of the studies (Curran et al., 2016; Gabel et al., 2016; Gaudreault et al., 2020; Myllyviita et al., 2019; Winter et al., 2017) reviewed the model by Chaudhary et al. (2015), which is a previous version of Chaudhary and Brooks (2018). The study by Lindquist et al. (2016) and Souza et al. (2015) analyzed an even earlier version by de Baan et al. (2013a). Crenna et al. (2020) included Chaudhary and Brooks (2018) in their study, but only to a superficial depth, meaning no case study testing was done and only a general mention of what the model does or already known general criticisms were reiterated. Similarly, the review by Kok et al. (2020) analyzed some gaps in Knudsen et al. (2017) but at a very high-level with no testing done. The study by Hayashi (2020) tested the Chaudhary and Brooks (2018) model, but did not compare it to other models (although they compared it to field-scale measurements but for rice paddies in Japan). Most did not focus on the applicability of the models for agricultural land use pressures, and the only ones that did were Kok et al. (2020), FAO (2020) and Gabel et al (2016). As mentioned previously, Kok et al. (2020) did not conduct an in-depth review and Gabel et al. (2016) did not review the most updated version of the model, Chaudhary and Brooks (2018). The report by FAO (2020) recommended the use of Chaudhary and Brooks (2018) for biodiversity loss due to livestock production systems given the wide range of characterization factors available for almost all ecoregions around the world, allowing the whole supply chain (mostly imported feed) to be accounted for, and given that land use intensity classes were included. However, no case studies were published to test its performance in this report. Koellner et al. (2013) and Teixeira et al. (2016) provided general guidelines on how biodiversity assessments should be carried out using LCA methodology, thus no review of the three relevant models were completed.

Ultimately, this study brings new light and research on specific top-down life cycle impact assessment models currently recommended by experts, as well as other models that estimate biodiversity loss from the bottom-up, using case studies of livestock production systems in Europe.

3.3 MATERIALS AND METHODS

3.3.1 OVERVIEW OF LCIA METHODS FOR BIODIVERSITY LOSS IN AGRICULTURAL SYSTEMS

First, the literature review by FAO-LEAP (FAO, 2020) and the experts in the EC Environmental Footprint Technical Advisory Board (European Commission, 2022) were consulted in order to identify, the currently recommended LCIA models that could be used to estimate biodiversity loss due to livestock production in Europe. This resulted in three main LCIA models summarized in

Table 12, categorized as top-down or bottom-up approaches. All methods use “land use” as the elementary flow to estimate biodiversity loss.

The Chaudhary and Brooks (2018) model uses the countryside species-area relationship (c-SAR) to calculate global characterization factors (CFs) in the units potential species loss per m^2 (PSL) due to land use associated with a product or service’ life cycle. This model projects PSL of five taxa (mammals, birds, amphibians, reptiles, plants) due to five broad land use types (managed forests, plantations, pasture, cropland, urban), under three intensity levels (minimal, light, intense) across 804 terrestrial ecoregions.

The model by Kuipers et al. (2021) adapted the c-SAR applied in Chaudhary and Brooks (2018) to include not just land occupation and transformation, but also fragmentation effects, using the species-habitat relationship (SHR). Fragmenting natural habitat has been found to reduce the viability of the natural species community (Bartlett et al., 2016; Crooks et al., 2017; Newbold et al., 2015) hence the importance to include it in biodiversity assessments. A new set of characterisation factors were developed for 702 terrestrial ecoregions, four land-use types (urban, cropland, pasture, forestry) and four vertebrate taxonomic groups (birds, reptiles, amphibians, mammals, plus the aggregate of these groups).

With respect to the bottom-up approach, the Knudsen et al. (2017) model was analysed. This model developed CFs for organic and conventional agricultural production, based on standardised sampling of plant species richness in organic and conventional farms across six countries in Europe within the temperate broadleaf and mixed forest biome, thus is applicable across a much larger region than the other studies. Characterisation factors (CFs) were developed for arable crops, mixed pastures, grass-dominated pastures and hedges using vascular plants as a proxy for biodiversity. This was the only LCIA model that was based on real species richness measurements using standardized techniques, making them inherently certain in terms of predicting species richness, hence is a good candidate for estimating biodiversity loss due to pasture-based livestock production from the bottom-up.

Table 12. Top-down and bottom-up LCIA Models estimating biodiversity loss.

Approach	LCIA method	Spatial resolution of impact assessment	Endpoint (E) or Midpoint (M)	Impact categories for biodiversity	Metric/indicator of impact	Relation to categories of EBVs	Taxa coverage
Top-down	Countryside-SAR with Land-use intensities (Chaudhary and Brooks, 2018)	country, ecoregion, global	E	Land use	PDF·m^{-2} (occupation); PDF·year·m^{-2} (transformation)	Community composition	Plants Mammals Amphibians Reptiles Birds
	Species-habitat relationship (Kuipers et al., 2021)	Global, ecoregion	E	Land use	PDF·m^{-2} (occupation); PDF·year·m^{-2} (transformation)	Ecosystem level	Birds Mammals Amphibians Reptiles
Bottom-up	LU impacts on plant species in Temperate Broadleaf and Mixed forest biome (Knudsen et al., 2017)	Biome, country, region, local	M	Land use	PDF·m^{-2} (occupation)	Community composition	Plants

3.3.2 CASE STUDY DATA

Second, case study data was gathered for lamb meat production from the Organic-PLUS research project (H2020 Grant agreement 774340, https://organic-plus.net/) and the Institute of Agri-food

Research and Technology (IRTA) in Spain. Data from the Organic-PLUS project yielded one case study farm for organic lamb production in Vanse, Norway (will be called NO1 hereafter), and data from IRTA yielded two case study farms for conventional lamb production in Spain. These case studies were chosen due to data availability and the fact that they are all based in the same biome, Temperate broadleaf and mixed forests biome, which is useful when applying the Knudsen et al. (2017) model which have CFs for this biome, allowing for greater consistency between the studied LCIA models. Details of each case study can be found in Table 13 and extra details in Table C-1. The NO1 case study produces certified organic meat from old Norwegian short tail landrace and Norwegian White Sheep breeds with winter housing and purchased feed and on-site fodder production, and summertime grassland grazing. The study area has a mean annual temperature of 7.1°C and an annual precipitation of 1280 mm. The soil group is cambisol and leptosol and the altitude is 6 m.a.s.l.

The two case studies in Spain are in the same province (Lleida) within 20 km straight-line distance of each other, one in Anás, Lleida (ES1) and one in Castellbó, Lleida (ES2), differing greatly in land occupation and feed types, thus making them good case studies for comparing effects CFs on biodiversity damage potential without confounding effects of pedoclimatic parameters. ES1 produces meat from Xisqueta and Aranesa sheep breeds with winter housing and alpine meadow grazing, with no feed produced on-site, only purchased feed is consumed. ES2 produces meat from the Barbarina breed with winter housing and purchased feed and on-site fodder production, and summer grazing mainly on alpine meadows and bushy areas. The altitude of ES1 is 1078.4 m.a.s.l. and 802 m.a.s.l. in ES2, and both have cambisol soil.

The type and quantity of the feed in each case study was based on real data from each farm. However, the ecoregion origin (where the feed was cultivated) of imported feed was not known in case studies ES1 and ES2, thus estimates were made based on data from Subdirectorate General for International Merchandise Trade (2019), Ministry of agriculture fisheries and food (2019), and the Secretary of State for Trade statistics on foreign trade in goods of Spain (Secretary of State for Trade statistics, 2022) (Table C-2). To calculate the kg/ha of each feed (e.g., wheat production in Spain or soy in Brazil), national yield statistics from the United Nations Food and Agriculture Organization (FAOSTAT) (Food and Agriculture Organization, 2022) was used. An average was taken over five years from 2015 – 2020 for those relevant countries (Table C-2). For the NO1 case study, information was provided by the farmers regarding which feed ingredients were locally produced and which were imported (all were local except soy and sugarcane). The origin of imported feed was unknown, thus, FAOSTAT (Food and Agriculture Organization, 2022) data was used to determine the main countries from which Norway imports soy (Brazil and Canada accounted for 97% of all soy imports) and sugarcane (Mozambique, India, Guatemala, Pakistan and Sudan account for 81%, the remaining percentage was distributed among nine other countries contributing between 0.0002-6% to the total, thus were not included). FAOSTAT (Food and Agriculture Organization, 2022) was also used to determine the yield in kg/ha for both local and imported feed for NO1, taken as an average over five years 2015 – 2020 (Table C-3).

Table 13. Details of case study farms used to test the performance of biodiversity loss models. More detailed information can be found in Table C-1 in the Appendix.

Farm details	ES1		ES2		NO1	
Number of ewes, age >517 days (heads·year^{-1})	55		280		59	
Number of lambs, age 30-75 days (heads·year^{-1})	38		220		124	
Lamb yield, live weight (ton·farm^{-1}·year^{-1})	0.85		4.5		1.92	
Ewe yield, live weight (ton·farm^{-1}·year^{-1})	0.15		1.5		0.21	
Wool yield (ton·farm^{-1}·year^{-1})	-		-		0.275	
Stocking rate (number of animal heads·m^{-2})	0.0002		0.0002		0.0019	
Land use type	Area (m^2·head^{-1}·year^{-1})	Ecoregion	Area (m^2·head^{-1}·year^{-1})	Ecoregion	Area (m^2·head^{-1}·year^{-1})	Ecoregion
Pasture	2.01E+03	Pyrenees conifer and mixed forests	1.17E+03	Pyrenees conifer and mixed forests	2.05E+02	Sarmatic mixed forests
Stable for animals	8.46E-01	Pyrenees conifer and mixed forests	2.24E-01	Pyrenees conifer and mixed forests	2.71E+00	Sarmatic mixed forests
Stable for farming equipment	1.69E+00	Pyrenees conifer and mixed forests	-	-	-	-
Feed grown on-site	0	-	3.60E+01	Pyrenees conifer and mixed forests	1.53E+02	Sarmatic mixed forests
Purchased complementary feed for ewes, rams and gimmers					Purchased feed for all animals	
Maize	3.48E+00	East European Forest steppe	3.05E+00	East European Forest steppe	-	-
	3.22E+00	Cerrado	2.82E+00	Cerrado	-	-
	6.86E-01	Northeastern Spain & Southern France Mediterranean forests	6.01E-01	Northeastern Spain & Southern France Mediterranean forests	-	-
Barley	1.64E+01	Iberian sclerophyllous and semi-deciduous forests	8.99E-01	Iberian sclerophyllous and semi-deciduous forests	5.51E-02	Sarmatic mixed forests
Purchased compound feed for lamb					-	-
Oat	-	-	-	-	4.77E-01	Sarmatic mixed forests

Maize	4.66E-02	East European Forest steppe	3.77E-02	East European Forest steppe	-	-
	4.32E-02	Cerrado	3.49E-02	Cerrado	-	-
	9.19E-03	Northeastern Spain & Southern France Mediterranean forests	7.43E-03	Northeastern Spain & Southern France Mediterranean forests	-	-
Wheat	3.25E-01	Iberian sclerophyllous and semi-deciduous forests	2.63E-01	Iberian sclerophyllous and semi-deciduous forests	5.45E-01	Sarmatic mixed forests
Barley	3.17E-01	Iberian sclerophyllous and semi-deciduous forests	2.56E-01	Iberian sclerophyllous and semi-deciduous forests	-	-
Soy	1.71E-01	Cerrado	1.38E-01	Cerrado	7.73E-01	Cerrado
	1.11E-02	Central forest/grasslands transition zone	1.07E-01	Central forest/grasslands transition zone	2.15E-01	Southern Great Lakes forests
Palm oil	1.07E-04	Sumatran peat swamp forests	8.62E-05	Sumatran peat swamp forests	-	-
Rye	-	-	-	-	2.34E-01	Sarmatic mixed forests
Peas	-	-	-	-	5.95E-02	Sarmatic mixed forests
Green beans	-	-	-	-	2.92E-02	Sarmatic mixed forests
Sugarcane	-	-	-	-	2.54E-03	Maputaland coastal forest mosaic
	-	-	-	-	1.13E-03	Upper Gangetic Plains moist deciduous forests
	-	-	-	-	6.45E-04	Central American dry forests
	-	-	-	-	1.27E-03	Northwestern thorn scrub forests
	-	-	-	-	7.33E-04	Sahelian Acacia savanna

3.3.3 ESTIMATION OF BIODIVERSITY LOSS DAMAGE

Third, we calculated the biodiversity loss due to land use of each case study, in three different ways, applying relevant characterization factors (CFs) from Chaudhary and Brooks (2018), Kuipers et al. (2021) and Knudsen et al. (2017) (See Appendix Table C-4, Table C-5, Table C-6 for a list of all the relevant CFs used in the present study). Sensitivity analyses comparing the use of different CFs were also carried out to observe the influence they may have on the biodiversity loss damage potential. Specifically, the sensitivity of different management intensities in both Chaudhary and Brooks (2018) and Knudsen et al. (2017). The global average occupation CFs were used from Chaudhary and Brooks (2018) and Kuipers et al. (2021), since these also accounted for vulnerability scores and global extinction probability, respectively. Additionally, impacts due to land transformation were not estimated since, to the best of our knowledge, no transformation of land has occurred in at least the last 10 years in each case study. Included in the scope of the LCA was the land area used for feed production on- and off-site, pasture grazing, and stables. The area $m^2 \cdot head^{-1} \cdot year^{-1}$ of each land use type and the yield of co-products in each case study can be found in Table 13 and the area in $ha \cdot farm^{-1} \cdot year^{-1}$ as well as other information can be found in Table C-1 (Appendix), where the latter was used to estimate the potential biodiversity damage of each case study per farm per year. All foreground pasture, on-site fodder production and urban stables was set to “minimal” intensity, whereas the land use intensity for feed varied (Table C-1); these intensities were chosen according to the classification described in Chaudhary and Brooks (2018). For example, organic production may be classified as “minimal” since little to no inorganic fertilizer nor pesticides are added in this class. However, Chaudhary and Brooks (2018) also state that organic farms in developed countries often fall within the “light” intensity class, but this would mean that pesticides or inorganic fertilizers would be added though to a smaller extent compared to intense use.

Then, to estimate the potential biodiversity damage of lamb meat, a functional unit of 1 kg lamb live weight (LW) was used and economic allocation was utilized to attribute impacts amongst multiple co-products in the system where values can be found in Table 14. Allocation based on physical attributes like mass was excluded due to the very different characteristics of meat and wool. Therefore, economic allocation was considered as the most reasonable way to distribute the environmental impact between co-products.

Table 14. Commercial prices per kg of animal live weight (LW) used for the economic allocation of biodiversity damage potential impacts.

Products	Price		
	ES1 (€/kg)	ES2(€/kg)	NO1 (NOK/kg)
Lamb LW	2.87	2.87	48
Ewe LW	1.15	1.15	21
Ram LW	2.04	2.04	-
Wool	-	-	20

Throughout this chapter, we highlight major limitations in each model in the way that they quantify impacts on biodiversity, and the suitability of each approach and model according to different goals and scopes, using the results from the case studies. Recommendations for improvements and further research were suggested.

3.4 RESULTS

3.4.1 HOTSPOT ANALYSIS

Using the two top-down models (Chaudhary and Brooks, 2018; Kuipers et al., 2021) to conduct a hotspot analysis, pasture land use was found to be the most contributing factor to PSL in both Spain and Norway (Figure 12). Despite using only purchased and imported feed in case study ES1, this feed only contributed 0.1% and 0.3% to the total PSL, using Chaudhary and Brooks (2018) and Kuipers et al. (2021), respectively, due to the small amount of land area required to produce the feed consumed compared to the pasture area (~300x more) (Table C-1). The Kuipers et al. (2021) model did not have any available CFs for urban land use in the ecoregion PA0433, thus, could not be accounted for in the contribution analysis (Figure 12B and Figure 12D). Nevertheless, using the urban CFs in the Chaudhary and Brooks (2018) model, land use for stables contributed very little overall, amortized over a 50 year lifespan (0.003%, 0.0001%, and 0.01% in ES1, ES2, NO1, respectively). Case study ES2 consumed both purchased feed and on-site fodder, yet, the on-site fodder only contributed 3.91% using the Chaudhary and Brooks (2018) model and 3.11% using the

Kuipers et al. (2021) model. These low percentages were due to the small land area used to cultivate the fodder (6 ha·farm^{-}1·year^{-1}) compared to the land area used for pasture (195 ha·farm^{-}1·year^{-1}).

In case study NO1, the land area used for pasture (7.2 ha·farm^{-}1·year^{-1}) and on-site fodder production (5.4 ha·farm^{-}1·year^{-1}) was similar in quantity, resulting in a higher proportion of on-site fodder contribution to PSL compared to ES2 using both the Chaudhary and Brooks (2018) and Kuipers et al. (2021) models with 36.44% and 43.69%, respectively (Figure 12E and Figure 12F). The purchased feed in NO1 also had higher contributions to the total farm PSL compared to ES2 with 2.62% and 6.35% for the Chaudhary and Brooks (2018) and Kuipers et al. (2021) models, respectively. These contributions were mainly due to soybean cropland use in Brazil, where 271.6 m^2·farm^{-1}·year^{-1} is required. Using the Chaudhary and Brooks (2018) model, the contribution of pasture land use was 24.49% larger than on-site fodder production. However, using the Kuipers et al. (2021) model the difference was much smaller, 6.26%. This incongruency was due to the difference in CFs between pasture and crop land use; in Chaudhary and Brooks (2018), the CF for minimal pasture land use was higher than the minimal cropland use, whereas the opposite was found in Kuipers et al. (2021). Moreover, the difference between the CFs is much smaller in Kuipers et al. (2021) (1.72E-17 PSL/m^2) compared to Chaudhary and Brooks (2018) (2.52E-15 PSL/m^2) (Table C-4, Table C-5 in the Appendix).

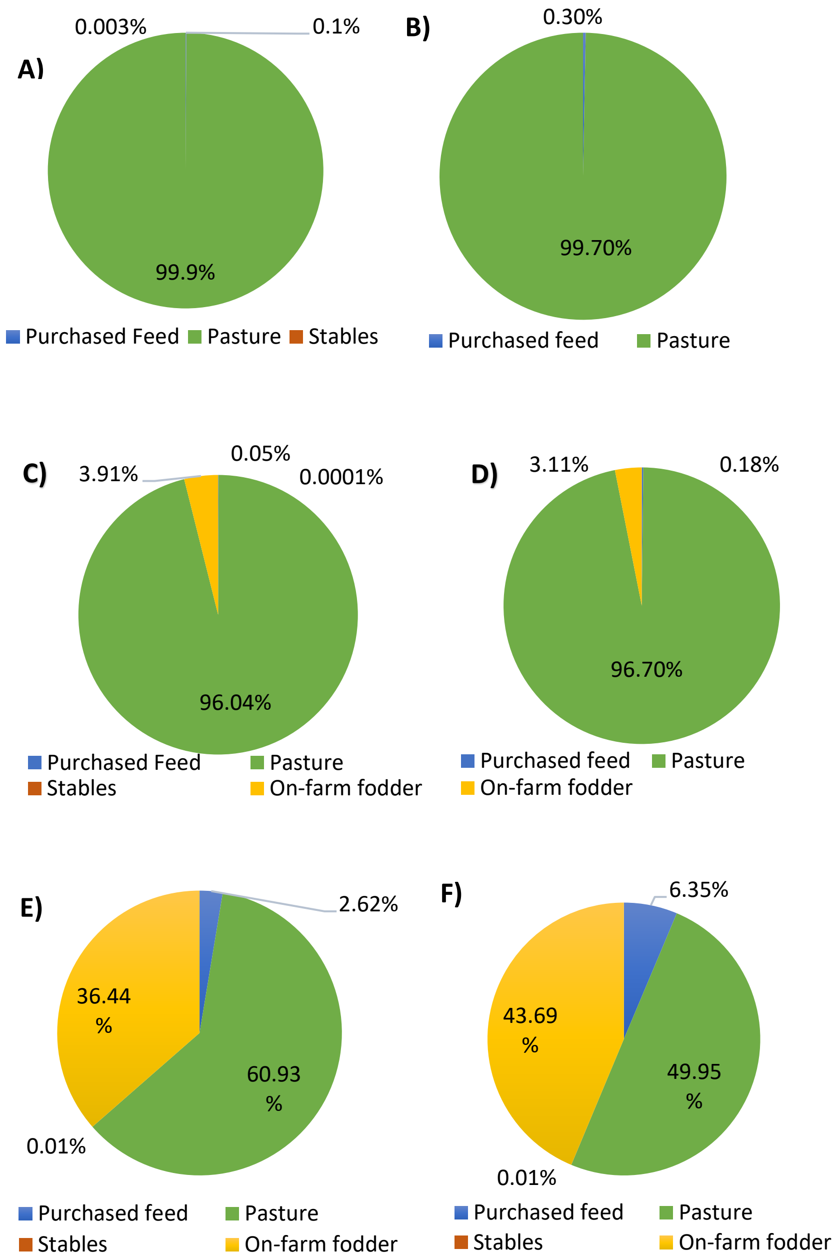


Figure 12. Contribution of different land uses to total aggregated mean potential species loss on sheep farms using the model by Chaudhary and Brooks (2018) in the first column case studies ES1 (A), ES2 (C) and in NO1 (E), and the model by Kuipers et al. (2021) in ES1 (B), ES2 (D) and in NO1 (F). Not all LCIA models had available CFs for all land use types, thus a legend was provided for each graph.

3.4.2 TOP-DOWN: CHAUDHARY AND BROOKS (2018)

Figure 13 shows the mean PSL per kg of lamb (LW) by taxa, using the Chaudhary and Brooks (2018) model for each case study. All impact scores across all case studies were statistically different from zero since the 97.5% confident interval did not cross the CF = y-axis.

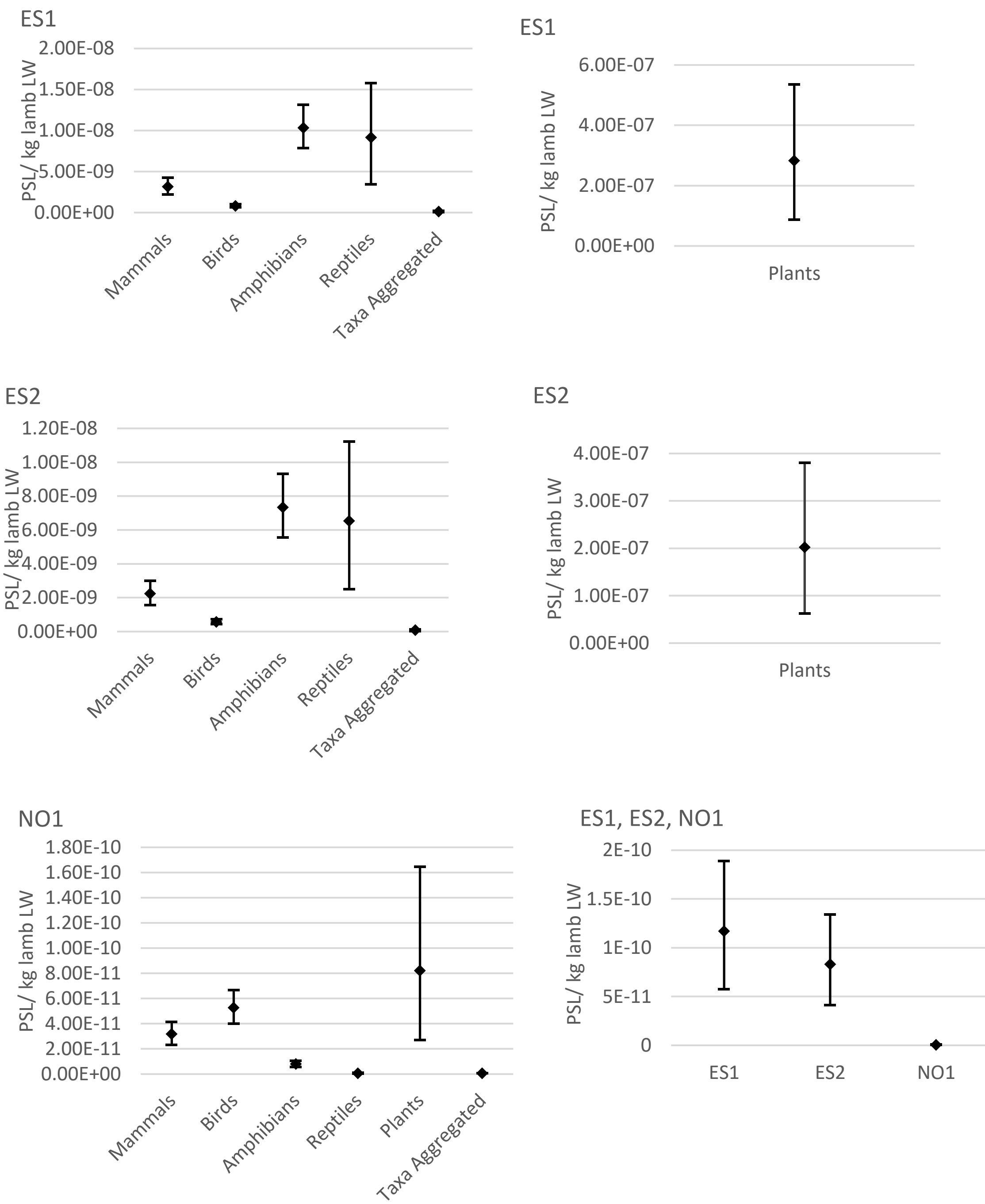


Figure 13. Potential species loss per kg of lamb live weight (LW) and 97.5% confidence interval by taxon using the model by Chaudhary and Brooks (2018) in case studies ES1, ES2 and NO1, and a comparison between the taxa aggregated PSL scores across all case studies (ES1, ES2, NO1).

In case studies ES1 and ES2, the impact of land use on PSL was significantly higher (statistically) for the plant taxon compared to the other taxa, as the 97.5% confidence interval did not overlap with the impact score of the other taxa (Figure 13). The high PSL of plants was mainly due to this taxon bearing the highest CFs amongst all relevant ecoregions and land use types. Following after plants, amphibians may also be highly impacted by pasture and on-farm fodder land use with high CFs mainly in the ecoregion NT0704 in Brazil. Reptile PSL were also on the same magnitude as amphibians, with the mean PSL being slightly lower, though the 97.5% confidence interval overlapped between the two taxa. The bird taxon had statistically the lowest PSL/kg lamb in the Spanish case studies compared to the other taxa, as the 97.5% confidence interval did not overlap with the impact score of any of the other taxa. The order from highest to lowest PSL by taxa can be explained by the CFs, which follow the same exact trend (Table C-4). Plants, amphibians and reptiles presented the most vulnerable characterization factors, which could guide us towards some compensatory protection policy of protection of said species.

In case study NO1, plants still had the highest mean PSL per kg lamb (LW) using the Chaudhary and Brooks (2018) model, although the 97.5% confidence interval overlaps with the mammal and bird taxon, showing that it is not significantly higher than these two taxa, but can be significantly higher than amphibians and reptiles (Figure 13). Differing from the trend of impact scores by taxa in Spain, birds were the second highest affected taxon, followed by mammals, although as previously mentioned, the PSL of plants, birds and mammals could not be statistically differentiated. The impact score of amphibians and reptiles were significantly lower statistically than the other taxa, where reptiles had the lowest impact score, even statistically different from amphibians. The order from highest to lowest PSL by taxa can be explained by the CFs, which follow the same exact trend. The CFs for plants were between one to three orders of magnitude higher than the other taxa in both pasture and crop land use types (Table C-4). The pasture CFs for birds was also between one to three orders of magnitude higher than the other taxon. For cropland, bird CFs were higher than the other taxon (except plants) across all intensities albeit of the same order of magnitude as mammals and amphibians. Reptiles had the lowest CFs of all taxa, differing by 1-3 orders of magnitude.

Using the taxa aggregated CFs from Chaudhary and Brooks (2018), the PSL/kg lamb LW of case study NO1 was significantly lower statistically than case studies in Spain (Figure 13). The mean PSL for ES2 was lower than ES1, but not statistically different. This follows the same trend as the land area used for feed and pasture, from lowest to highest, NO1 (695 $m^2 \cdot head^{-1} \cdot year^{-1}$), ES2 (1217 $m^2 \cdot head^{-1} \cdot year^{-1}$) and ES1 (2044 $m^2 \cdot head^{-1} \cdot year^{-1}$) (Table 13).

Additionally, a sensitivity assessment was carried out to test the sensitivity of the CF's intensity classes in Chaudhary and Brooks (2018) across all case studies. Since pasture and on-farm fodder production were the most impacting land use types (Figure 12), only these were tested for intensity sensitivity. They may be classified as either minimal or light, thus, results are only shown for these two classes (Figure C-1). The 97.5% confidence interval of minimal intensity overlapped with that of light intensity across all species groups and taxa aggregated score, meaning there was no statistical difference between the impact score of the two intensity classes (Figure C-1).

In regards to the ability of the Chaudhary and Brooks (2018) model to differentiate between land use types, case study NO1 was used since the land area of pasture and fodder were similar. The 97.5% confidence interval of mammals, amphibians, reptiles, plants and the taxa aggregated score overlapped when comparing pasture and fodder land use, meaning there was no statistical difference in the impact score between the two land use types (Figure 14). Birds was the only taxon where the confidence interval did not overlap, thus, was significantly different between the two land use types.

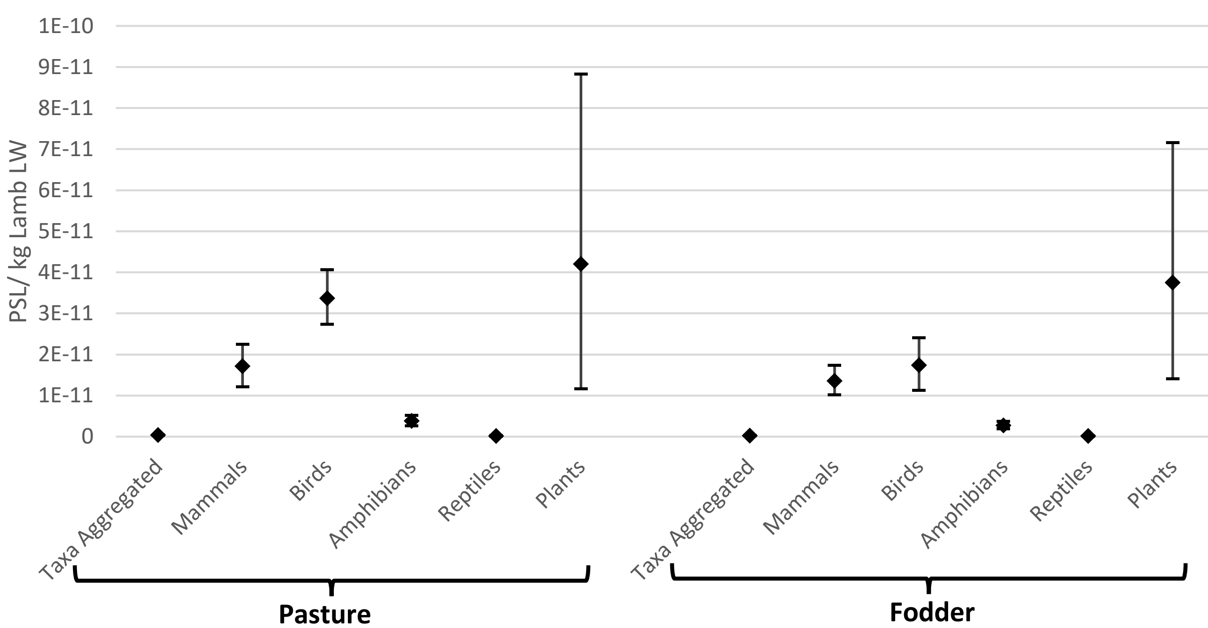


Figure 14. Potential species loss (PSL) per kg lamb live weight (LW) for pasture and fodder land use in case study NO1, using the Chaudhary and Brooks (2018) model.

3.4.3 TOP-DOWN: KUIPERS ET AL. 2021

Figure 15 shows the PSL per kg lamb (LW) by species type using the model by Kuipers et al. (2021), in case studies ES1, ES2 and NO1. This model does not have CFs for plants, and furthermore, no CFs at the lower and upper limit of confidence intervals were provided, thus, statistical differences between impact scores could not be discussed.

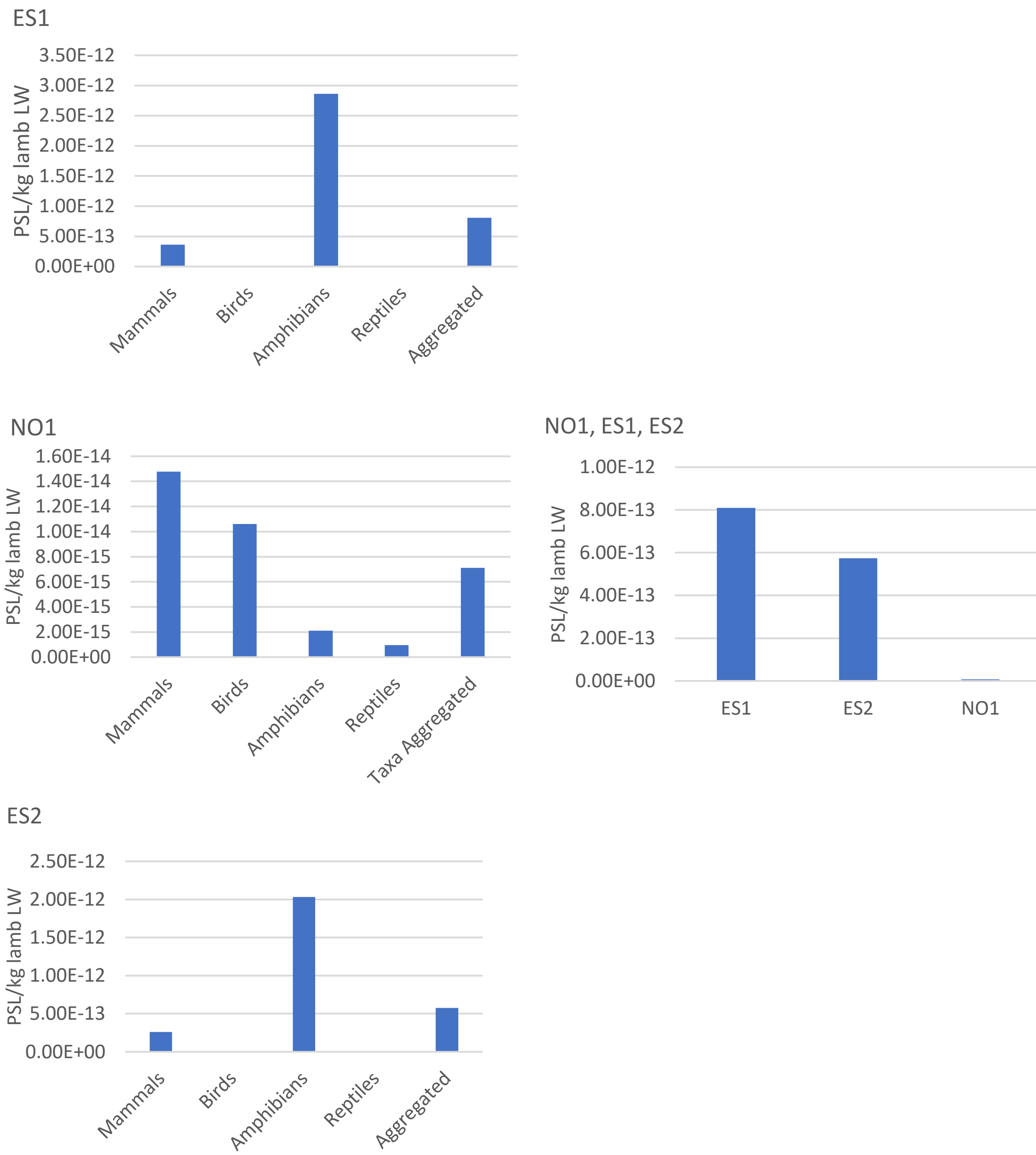


Figure 15. Potential species loss (PSL) per kg of lamb live weight (LW) by taxon using the model by Kuipers et al., (2021) in case studies ES1, ES2 and NO1.

In case studies ES1 and ES2, the PSL by taxa from highest to lowest were amphibians, mammals, birds and reptiles (Figure 15). In case study NO1, the mean PSL by taxa from highest to lowest were mammals, birds, amphibians and reptiles. This differs quite substantially from the trend seen using Chaudhary and Brooks (2018), where the mean impact scores from highest to lowest were plants, amphibians, reptiles, mammals and birds. However, taking into account the 97.5% confidence interval in Chaudhary and Brooks (2018), the PSL of reptiles overlaps with amphibians and mammals (but not between amphibians and mammals) thus PSL of reptiles could be above or below the other two taxa. On the other hand, the 97.5% confidence interval of amphibians does not overlap with mammals (nor birds in fact) and thus should be higher than mammals and birds, which is consistent with Kuipers et al. (2021). The only important inconsistency between the two LCIA models was the impact score for birds. According to Chaudhary and Brooks (2018) the impact score for birds had statistically the lowest PSL than all other taxon, however, in Kuipers et al. (2021) it was second to last, and instead reptiles had the lowest PSL. This was due to the reptile CFs for ecoregion PA0433 in Kuipers et al. (2021) having a value of zero PSL/m^2. Kuipers et al. (2021) state that a CF = 0 indicates no effect of the land use type on species richness, where the affinity of the species group equals 1, meaning that the land use does not decrease local species richness. This is the case when all species within the ecoregion are documented to occur in that land use type, according to the International Union for Conservation of Nature (IUCN) data (Personal communication).

Both top-down models Chaudhary and Brooks (2018) and Kuipers et al. (2021), were consistent in their ranking of the case studies in terms of PSL/kg lamb LW; ES1 > ES2 > NO1.

3.4.4 BOTTOM-UP: KNUDSEN ET AL. (2017)

The model by Knudsen et al. (2017) only evaluates one taxon, vascular plants, hence only the PDF of plants will be discussed here. Knudsen et al. (2017) provides CFs for intensive and extensive farming in both organic and conventional fields in the Temperate Broadleaf and Mixed Forests biome. The CFs from Knudsen et al. (2017) used to estimate the biodiversity damage in each case study are listed in Table C-6. The foreground pasture and on-farm fodder production of all case studies were located in this biome. However, CFs were not available for 11 out of 13 different feed types in ES1 and ES1, and 7 out of 13 feed types in NO1, since they did not originate from this biome (Table C-1).

In general, from highest to lowest PDF plants/kg lamb LW, the case studies are ranked NO1 >ES2 > ES1 when using pasture conventional extensive CFs for ES1 and ES2 and organic extensive CFs in NO1. This is the opposite of the ranking seen in the top-down models analyzed previously. This was mainly due to the CFs having a negative sign, indicating beneficial biodiversity effects. Hence, the more land used in these land use types with negative CFs, the lower the biodiversity damage, and the more beneficial it may be on plant biodiversity. The ranking of land area used for pasture and on-site fodder production was, from lowest to highest, NO1, ES1 and ES2, explaining the general ranking seen for the PDF plants/kg lamb LW. However, the ES1 and ES2 were not specifically consistent with the PDF results due to ES2 having higher yield (~5x higher).

Since pasture was the main contributor across all case studies and LCIA models (Figure 12), a sensitivity analysis was carried out to determine two specific effects that pasture land use can have on the PDF of plants: 1) the effect of choosing CFs of different farming practices (organic or conventional), 2) the effect of choosing CFs of different intensities. Although case studies ES1 and ES2 were not certified organic, the results shown in Figure 16 was a simple exercise to demonstrate the difference between CFs for organic and conventional farms. Yet, almost all practices in ES1 and ES2 were compliant with the European Commission’s regulations on organic livestock farming(European Commission, 2008a), except for the origin of the feed which was not from organic farms.

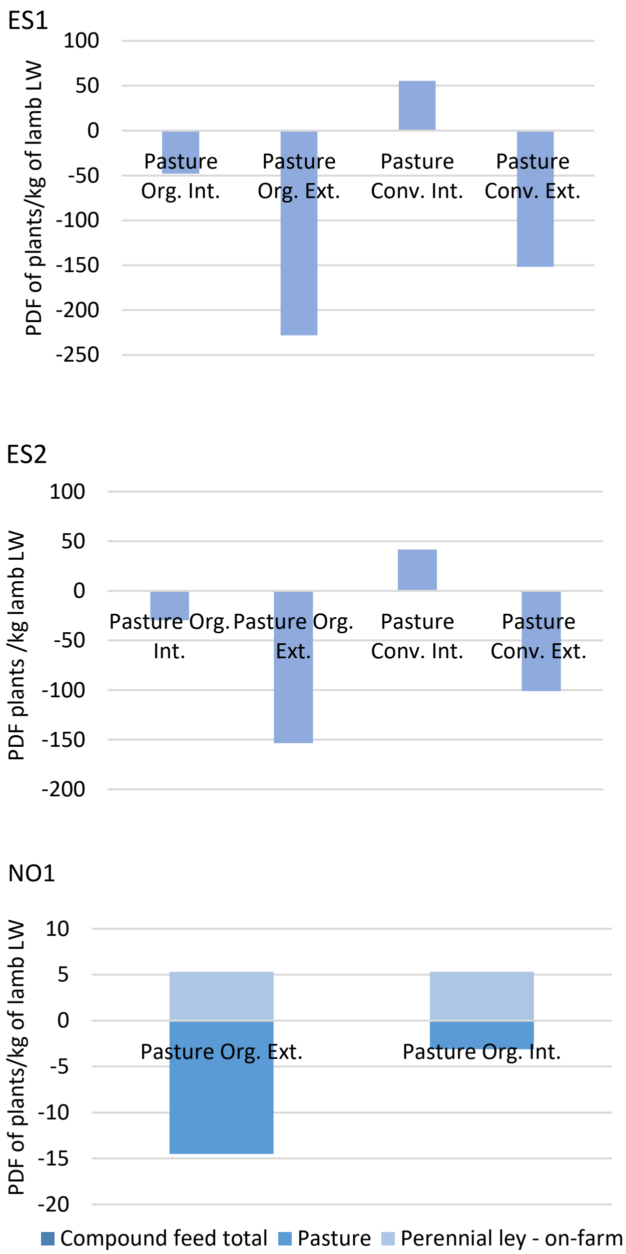


Figure 16. Potential disappeared fraction (PDF) of vascular plants per kg of lamb live weight (LW) for case studies ES1, ES2 and NO1, using CFs from the model Knudsen et al. (2017)

In regards to the first point, organic CFs for pasture land use were lower than their conventional counterparts (when comparing intensive with intensive and extensive with extensive on the biome-level, Table C-6), resulting in lower PDF of plants per kg of lamb LW in both ES1 and ES2 case studies (Figure 16).

The CF for conventional extensive pastures was lower than that for organic intensive pastures, resulting in lower PDF per kg of lamb LW, illustrating the importance of including intensity sub-classes within organic and conventional classes, as organic farms may not always have higher species richness. However, it must be mentioned that the "intensive" class only covered Germany (16 farms surveyed) in Knudsen et al. (2017), whereas the extensive pasture data covered four European countries (54 farms surveyed), therefore, data may not be as reliable. As exemplified in Figure 5, choosing extensive CFs over intensive ones can result in impact scores ~5x less in organic farms or can even have the opposite sign in the case of conventional farms where intensive had positive impact scores and extensive had negative scores, across all case studies. Therefore, it is important to properly classify the intensity of the farm being studied.

3.5 DISCUSSION

This study was conducted to initiate research on the application of biodiversity loss indicators to agriculture, where, currently, there are no other studies that allow the results to be compared. A priori, the comparison between the three case study farms could lead us to conclude that NO1 had lower PSL impact per FU followed by ES2 and ES1, due to lower land use, using the two top-down models (Figure 12, Figure 14Figure 13). This occurred despite lower lamb yield in NO1 compared to ES2 (~2x lower), showing that the difference in land use was sufficient enough to cancel out the effects of lower yield on PSL. On the contrary, using the bottom-up model by Knudsen et al. (2017), ES1 had lower PSL per FU followed by ES2 and NO1, due to the differences in yield, showing that yield can influence the results in this case. The fact that the top-down and bottom-up models do not yield the same trends when comparing livestock products demonstrates the need to adequately choose which model is more suitable to the goal and scope of the study, keeping in mind the goal and scope of the models themselves and their limitations. Therefore, the discussion has been divided into three sections: 3.5.1 Top-down, 3.5.2 Bottom-up and 3.5.3 Further research.

3.5.1 TOP-DOWN

In general, the top-down indicators recommended by the EC Environmental Footprint Technical Advisory Board(European Commission, 2022) and LEAP-FAO(FAO, 2020) can help highlight hotspots and general trends, for example, that plant species, amphibians and reptiles are the taxa with the highest risk in the studied areas, hence policies in this regard should be prioritized. Moreover, these indicators can be used to check the broad difference between PSL due to different land uses within specific ecoregions or countries, by looking at the trends in CFs. For example, in ecoregion PA0433, minimal pasture has the lowest mean taxa aggregated CF out of all agricultural and forestry land use types, in both Chaudhary and Brooks (2018) and Kuipers et al. (2021).

As previously discussed, the production of feed and complements may have very low importance when grassland livestock is defined as the foreground system of study (Figure 12). The main contributor to biodiversity loss in these case studies were pasture and on-farm fodder production, due to the high amount of land required compared to compound feed. This correlates with the findings in other livestock studies where pasture and on-farm fodder production was the main contributor to livestock products in Europe rather than the feed (Kok et al., 2020; Leip et al., 2015). Since the complementary and compound feed consumed was a mixture of various ingredients from many different countries, the land use required to grow that specific ingredient was very low compared to pasture land use, e.g., in ES1, 0.0032 ha/farm/year of soy from Brazil or 0.022 ha/farm/year of maize grain from Ukraine compared to 50 ha/farm/year of pasture. If fodder is grown on the farm using land area similar to that of pasture (of the same order of magnitude), then fodder can have similar PSL to pasture use, as seen in case study NO1. If the area of the fodder is significantly lower than the pasture area (of different orders of magnitude, e.g., 2), or non-existent, then compound feed may contribute maximum ~4% to the total biodiversity loss impact, such as in case studies ES1 and ES2. In addition, the Chaudhary and Brooks (2018) CFs for minimal pasture intensity in ecoregion PA0433 were generally higher than all other relevant CFs for cropland, except those for cropland in ecoregion IM0160 for mammals, birds and taxa aggregated. Hence, both the high land area and CFs for pasture yielded higher PSL for minimal pasture use in PA0433 compared to cropland use, though the CFs played a much smaller role due to similar orders of magnitude in CFs in some ecoregions. Therefore, this shows that background processes such as feed in livestock systems cannot be captured very well due to the land use areas being distributed among many ingredients, resulting in very low land use areas and hence low PSL. What is actually being shown in Figure 12 is a fraction of the PSL that is occurring in, e.g., Brazil due to soy production, where the fraction represents the amount consumed on the livestock farm. Since these land areas are not actually representative of the real land used for, e.g., soy feed in Brazil, and if our goal is to also find out the extent of the damage there, we would need to analyze soy production as the foreground system. Since our goal here is to estimate the PSL due to lamb production in Spain or Norway, only the fraction of PSL due to feed is shown.

To find out which ingredient in the feed is the most important, a hotspot contribution analysis should be done on the different feeds themselves, excluding the foreground system. In ES1, the barley grain from Spain would be the most important in the complementary feed (63%), and as for the fattening lamb feed, Brazilian soy (33%), Spanish wheat (27%) and Spanish barley (27%) would be the most important in terms of PSL on the farm, using the model by Chaudhary and Brooks (2018) (Figure C-2). In ES2, Brazilian maize grain would be the main hotspot in the complementary feed (68%, the remaining contribution split among the other three ingredients), and as for the lamb feed, the same trend was seen as in ES1 (Figure C-2). In NO1, Brazilian soy was the main hotspot (81%) with the remaining contribution split among the other nine ingredients (Figure C-2). The same trends were seen using the Kuipers et al. (2021) model (Figure C-3). Thus, these two top-down models can be a great indicator for hotspot analysis, keeping in mind that it only shows just that, which land use contributes the most to the total PSL of that product, and not that one feed crop in the system may be more damaging than the other (e.g., Brazilian soy vs. Spanish wheat); for this comparison, a foreground analysis must be done for both products.

It is also interpreted that the differences between the characterization factors for the different land uses and corresponding intensities are relatively low and what really influences PSL is the amount of occupied area. In Chaudhary and Brooks (2018) and Kuipers et al. (2021) this was due to the fact that they depend too much on the proportion of area of a specific type of land use, and not enough on the taxonomic affinity or the intensity of management (in the case of Chaudhary and Brooks (2018)). Specifically, regional land occupation CFs in Chaudhary and Brooks (2018) are calculated by multiplying an allocation factor by the projected species loss for a specific species in that ecoregion, divided by the area of that land use type in that ecoregion. The allocation factor (denoted as $a_{i,j}$ in their study, where i is the land use type and j is the ecoregion) represents the area share of a specific land use type (e.g., cropland) within a specific ecoregion (e.g., Pyrenees conifer and mixed forests). Since the area of any land use type compared to the total area of an ecoregion would usually yield an extremely small value, the final allocation factors $a_{i,j}$ would also be extremely small. These allocation factors are much smaller than the other variables that the CF depends on, such as taxon affinity (usually between -1 and -3 orders of magnitude) or proportion of land use type under a specific management intensity (-1 order of magnitude). This is the main reason why the CFs in Chaudhary and Brooks (2018) were consistently low on orders between -6 and -18. For example, in ecoregion AA0103, the area share of pasture would be 2.75×10^{-8}, leading to a regional land occupation CF for amphibians of 4.56×10^{-10} in Chaudhary and Brooks (2018). Therefore, the CFs in Chaudhary and Brooks (2018) rely much too heavily on the area share of a specific land use type, and not enough on taxon or habitat affinity or management intensity. This leads to the fact that, according to results in Chaudhary and Brooks (2018), it would be more important to save one m^2 of land use, than implement changes in management intensity, an aspect that could discredit the need for development of specific factors, so it could be deduced that the classification into six land uses and three intensities is still quite general and it would be interesting to have a more detailed approximation of different practices. In Kuipers et al. (2021), a similar allocation factor is used, called a distribution factor (denoted as $q_{g,i,j}$) to attribute the impacts on taxon *g* in region *j* to land use type *i*. The distribution factor is dependent on the habitat suitability and the area weighted by the suitability of land use type *i* to the taxon *g* in region *j*, relative to the total suitability weighted area of the land use types. Since average occupation CFs are calculated by dividing the $PDF_{g,j}$ by the total regional amount of LU and multiplied by $q_{g,i,j}$, it is the $q_{g,i,j}$ that largely determines the magnitude of the CFs, causing them to have orders of magnitude between -11 and -19 (or CF=0). Specifically, within the equation to calculate $q_{g,i,j}$, it is the $A_{i(lu)j}$ variable (area of LU type *i* in region *j*) that influences these low orders of magnitude, again showing that, similar to Chaudhary and Brooks (2018), the CFs rely very heavily on area of a specific land use type. However, the global extinction probability (GEP) variable can also influence global CFs in Kuipers et al. (2021) due to the high variability of GEPs (between 0 and -10 orders of magnitude). The GEP indicates the potential contribution of regional species loss to global species extinctions by considering endemism and the threat status of the regional species pools (Kuipers et al., 2021). Kuipers et al. (2021) do not have CFs for different management practices which means it is less suitable for agricultural LCAs, however, including them may not yield very different results unless the CFs were developed at higher resolution. Furthermore, the CFs in Kuipers et al. (2021) were not statistically distinct between different land use types, unless they are in different ecoregions. In Chaudhary and Brooks (2018), the CFs for agricultural land use types, pasture and cropland were also not well distinguished, stating that future studies should include further land use classes, but new high-resolution, harmonized and validated land use maps with different intensity types are needed. Kuipers et al. (2021) also state that, in regards to some of their CF = 0, that it is an artefact of the way they quantified the species affinities (i.e., based on the fraction of species in the ecoregion that are documented to occur in the land use type relative to the total number of species in the ecoregion). The carrying capacity or ecosystem quality (e.g., cropland habitat is lower than that of primary vegetation, even though the species is documented to occur in both habitats), is something that their method does not currently capture (Personal communication). Therefore, both top-down approaches may not be suitable for differentiating agricultural products from one another (e.g., cropland vs pasture, or minimal pasture vs. light pasture within the same ecoregion).

Another aspect to highlight is the variability of the characterization factors makes it difficult to clearly establish significantly better options. As the methods Chaudhary and Brooks (2018) and Kuipers et al. (2021) are based on characterization factors estimated at the ecoregion level, applying and extrapolating these factors to local levels has its limitations. It cannot explain the different microclimates, nor the local/regional values of species richness, taxa affinity and vulnerability. Therefore, these methods are mainly useful for comparisons at the ecoregion level e.g., for national or global assessments or companies, but not suitable for assessing other more qualitative changes such as the impacts of over- or under-grazing within an ecoregion, in corroboration with the guidelines given in the LEAP-FAO documents (FAO, 2020). This is supported by the review by (Gaudreault et al., 2020) who tested the CFs from a previously recommended biodiversity loss LCIA model published in 2015 by (Chaudhary et al., 2015) using corrugated cardboard as a case study. The model by Chaudhary and Brooks (2018) was based on the study by Chaudhary et al. (2015). Gaudreault et al. (2020) found that, “the local effect on species of forest management is likely to be misrepresented by the average number of species in a given ecoregion. Successful consideration of biodiversity response in the context of forest management would require the integration of other approaches, such as site-specific studies.” This criticism would still be applicable to the Chaudhary and Brooks (2018) model since they the same methods like countryside-SAR and the same datasets for total species richness at ecoregion level. Gaudreault et al. (2020) also recommend that Chaudhary et al. (2015) be improved by including management practices, which Chaudhary and Brooks (2018) integrated into their model, but judging by the results in the present study, the CFs still are not at a high enough resolution to give meaningful or representative results.

According to both top-down models, plants were the species most affected by land use pressures being statistically higher than the other taxa (except in case study NO1). Following plants are amphibians and reptiles. This is rational seeing as plants and other less mobile taxa are strictly reliant on soil or plant conditions, compared to highly mobile taxa like birds(Puig-Montserrat et al., 2017), thus would be most affected by land use practices. Moreover, they create and shape terrestrial ecosystems and its diversity correlates highly with other species groups' diversity (Duelli and Obrist, 1998). This supports the use of plants as a proxy for biodiversity loss in Knudsen et al. (2017).

However, many other less mobile taxa, such as invertebrates and arthropods, can be affected by land use practices to a greater extent(Puig-Montserrat et al., 2017; Rey et al., 2019) and new CFs should be made for these taxa in the future in all LCIA models. Taxon like birds have been found to rely more on landscape complexity of the farm than management intensity(Rey et al., 2019), thus, Kuipers et al. (2021) may be more suitable for this taxon since the model includes the effect of landscape fragmentation on PSL, and may be useful for any other taxa with high mobility and dispersal. Further limitations in the Chaudhary and Brooks (2018) model are discussed in Chapter 3.6.

3.5.2 BOTTOM-UP

In general, bottom-up approaches like in Knudsen et al. (2017), are much more certain in regards to biodiversity loss compared to top-down approaches since they are based on real field measurements of species richness in their respective land use types. The CFs are an actual reflection of species occurrence and inherently include the effects of management practices (e.g., organic or conventional farming) on species richness. In the top-down approaches studied here, an inference is made on potential species loss using ecoregion-level data which needs to be validated against real data, and its performance evaluated using different goodness fit metrics, although the authors state that the predicted endemic extinctions per ecoregion compare well with the species threatened with extinction in the IUCN Red List (International Union for Conservation of Nature and Natural Resources: Cambridge UK, 2022). For agricultural land use types, the framework by Knudsen et al. (2017) would be most suitable seeing as the CFs are based on real field measurements of species richness on pastures and cropland, unlike the top-down models. The Knudsen et al. (2017) model, among others (Elshout et al., 2014; Koellner and Scholz, 2008; Mueller et al., 2014; Schryver and Goedkoop, 2010), are the only ones that have CFs for conventional and organic crops and pastures, where the Knudsen et al. (2017) model is the only one with standardized measurement techniques. This is an important step forward for estimating the biodiversity impact of OA since the European Commission aims to have at least 25% of the EU's agricultural land under organic management by 2030 (European Commission, 2020a).

Due to the highly localized data in Knudsen et al. (2017), the uncertainty of bottom-up CFs increases when extrapolated to larger scales, like regions outside of Europe since only countries within Europe were taken into account . Nevertheless, many countries were covered in the biome of concern, thus may be quite certain in terms of estimating biodiversity loss in the Temperate broadleaf and mixed forest biome, but only in Europe. This is similar to the uncertainty in CFs for top-down approaches when applied to local situations due to their high resolution and inability to account for specific practices. The exact location nor the ecoregion from which the species richness data was gathered was not mentioned in Knudsen et al. (2017), thus, the CFs could not be differentiated by ecoregion level (there are seven ecoregions in this biome in the relevant countries). Therefore, this model cannot be used for hotspot analysis since there are no CFs for countries or ecoregions outside of Europe such as Brazil for soy-based feed, and as mentioned previously in section 3.4.4, CFs were not available for 11 out of 13 different feed types in ES1 and ES1, and 7 out of 13 feed types in NO1, since they did not originate from this biome. Moreover, no CFs were available at country level for Norway in Knudsen et al. (2017), though it is in the same biome. Vascular plant species richness in Norway may be higher than those found in Knudsen et al. (2017) for grassland pastures and in forested areas and the difference between the two are also similar(Kapfer et al., 2022; Myklestad and Sætersdal, 2004), thus the CFs for PDF may be lower in Norway. In the future, more data would be needed to develop CFs at ecoregion and biome level with higher certainty.

The review by (Kok et al., 2020) also describes some limitations in the Knudsen et al. (2017) model, but only at a high level without any in-depth testing. They found that since the model does not provide data on total plant species richness (only local species richness is given), landscapes that have many ecological structures like natural forest and pasture would have lower biodiversity damage scores than just pasture, whereas a mixture of both ecosystems would result in the highest total species richness, penalizing having such structures.

3.5.3 FURTHER RESEARCH

New CFs can be easily developed using the framework by Knudsen et al. (2017) if sufficient species richness data is available, and can be parameterized according to the types of land uses under study, and can even be applied across all geographical scales if more data becomes available. On the other hand, top-down approaches cannot be applied to local levels, since too many inferences would be made to reach each level, accumulating more uncertainty along the way. As Souza et al. (2015) state, robust and reliable CFs should be validated against or better yet, based on field data and national case studies. However, data availability is an important limitation in bottom-up approaches, thus, more investment in data gathering should be done if more certain assessments are to be made. Hayashi (2020) suggested that simple biodiversity field monitoring would be useful and compatible with bottom-up approaches, such as automatic species identification using machine learning. In general, a mixture of the two approaches could also be done; top-down approaches could be used for hotspot analysis, especially for background systems, and bottom-up for foreground systems. The choice between approaches or the combination of the two is driven by, 1) the goal and scope of your study, 2) the data available. If only high-level or national assessments are needed or data is available only at this level, then top-down assessments would be suitable. If the goal is to study local biodiversity loss due to agricultural land use on a particular farm or area, then bottom-up approaches would be suitable.

The top-down approaches studied here could not differentiate very well between cropland and pasture CFs, consequently leading to similar PSL in both LU types. Broad LU classes like cropland and pasture are not helpful when comparing specific agricultural products like annual or permanent crops, which have been seen to differ in plant species richness (Lüscher et al., 2016). Furthermore, the CFs for cropland do not differ much across the three intensity levels in Chaudhary and Brooks (2018), and as we have seen, they may sometimes be redundant since the CFs rely heavily on the area share of each LU type. Hence, these models could be improved by increasing the resolution and harmonization of the data, where specific suggestions were given in this chapter regarding how to include, for example, organic and conventional management practices. The CFs in Kuipers et al. (2021) depend on a couple of other factors than just the area share of each LU type (i.e., GEP and PDF), since the CFs were calculated using the Species habitat relationship (SHR), instead of the countryside-SAR (species-area-relationship) model adopted in Chaudhary and Brooks (2018). However, Kuipers et al. (2021) could be improved further by including management intensities, as it would be interesting to see if this would cause a greater difference between characterization factors for cropland and pasture. In order to establish more sustainable agricultural production practices, we must focus more on biodiversity impacts due to management practices rather than due to land use within an ecoregion.

Kuipers et al. (2021) could be very useful if the goal is to study the effect of land use and fragmentation on highly mobile taxa such as birds or mammals, where fragmentation would be a key factor (Rey et al., 2019). This study could be improved by including other mobile taxa like arachnids (e.g., spiders), insects especially pollinators (e.g., butterflies, bees), and plants (e.g., sexually reproducing plants).

Knudsen et al. (2017) treated all species as equal in weight, thus critically threatened species were not taken into account, unlike in Chaudhary and Brooks (2018) and Kuipers et al. (2021). The incorporation of threatened plant species would allow the CFs to be differentiated between land use types that have similar total species numbers but different number of threatened species. For example, the CFs in Knudsen et al. (2017) could underestimate the ecological value of ecosystems that have overall low species richness but carry many species with threatened status. The current methodology to account for threatened plant species in, for example, Chaudhary and Brooks (2018) and Kuipers et al. (2021), is through a calculation of vulnerability scores; the summed proportion of the range size for each species present in an ecoregion and weighted by their extinction risk classification using the IUCN Red List. Kuipers et al. (2021) take this further by incorporating the extent of occurrence, endemic richness, and range rarity, to calculate Global Extinction Probabilities (GEP). One bottom-up model by Koellner and Scholz(Koellner and Scholz, 2008, 2007) also incorporates threatened plant species by calculating species richness-based CFs (called ecosystem damage potentials, EDP) relative to a reference for both non-threatened and threatened plant species. These three aforementioned methods are based on the assumption that all threatened species present within each ecoregion or area will inevitably become extinct due to the applied land use pressure, meaning that the ecoregions or areas with threatened species are penalized and have higher CFs than those without threatened species. However, an important criticism to keep in mind is that these threatened species may exist in some areas compared to others due their affinity towards them and their favorable conditions, thus, possibly reducing extinction (Hobohm et al., 2021; Teixeira et al., 2016). Therefore, further research is needed on threatened species affinity towards specific land use types, and by extension, a focus on γ-diversity to compare local species richness in a smaller land use type to the broader land use type (useful for the three aforementioned methods). This will help validate or reduce the uncertainty of the assumption to penalize areas with threatened species. Nevertheless, these methods would still be a good proxy to predict threatened species loss patterns at the global scale, but not particularly useful at local scales as more specific data would be needed (e.g., threatened species affinity, a focus on γ-diversity). For example, both top-down models Chaudhary and Brooks (2018) and Kuipers et al. (2021), cautioned that the global CFs should be interpreted as a measure of *potential regional or global* species extinction and *not as explicit* predictions.

Other more general limitations across all models studied in this chapter, is the fact that they only cover one of the pressures that drive biodiversity loss, land use. They do not include other direct pressures such as climate change, invasive and non-native species, pollution, use of water bodies, direct exploitation of organisms, nor indirect pressures such as people's disconnect with nature and lack of value and importance of nature (IPBES, 2019). Moreover, all models will show that the more space per lamb, the higher the biodiversity damage, but this does not take into account the animal welfare, which increases as more area is made available. This is currently no considered in LCA in general. Additionally, all the models are based on the compositional aspect of biodiversity, species richness, when biodiversity is also composed of functional, genetic and ecological diversity. Possibly, the Kuipers et al. (2021) model can be adapted to create CFs for invasive species since a key factor in the spread of invasive species is often transport/dispersal distances(Essl et al., 2020). Distribution data can be found from IUCN's global invasive species database (http://www.iucngisd.org/gisd/) and a study by these studies (Rejmánek and Richardson, 2013; Turbelin et al., 2017). Habitat preference and dispersal would require more specific research but an example of invasive plant species dispersal data or models can be found here (Caton et al., 2022; Coutts et al., 2011; Davies and Sheley, 2007; Gosper et al., 2005; Higgins et al., 1996; Lee et al., 2022; Merow et al., 2011), but demographic factors (e.g., fecundity, survivorship and/or age of maturity (Coutts et al., 2011)) may also play an important role and may need to be included.

Furthermore, the total allocation of pasture land to the animal production system may be flawed, pastures may cover other functions related to ecosystem services apart from the basic one of providing food, such as regulation (avoiding erosion, water cycles, nutrients, pollinators, etc.), support (biological cycles, fire prevention), and culture (landscape aesthetics). Especially in mountainous regions, pastures may cover all of these functions, for example providing natural areas that are important for certain animals and plants that require grazing to proliferate, and landscape aesthetics. Kok et al. (2020) also explain that livestock can have many functions in different farms or areas around the world including food production, conservation/ecological intrinsic value, a mix of the two, or even cultural and financial functions. However, as the function of livestock in LCA is often food production, a life cycle approach is unlikely to be suitable for conservation functions, as it is difficult to quantitatively relate all flows in the inventory to a reference value for conservation. One example of how to account for the multi-functionality of sheep farming systems was done in Ripoll-Bosch et al. (2013) where services such as biodiversity and landscape conservation were valued based on EU agri-environmental subsidies and allocated GHG emissions per kg of lamb LW among the sheep farming systems. Focusing on other functions than just yield may help shift agricultural practices towards more sustainable ecological limits and lower the yield benchmark, leading to the “true yield gap” between organic and conventional food products (Seufert et al., 2012) discussed in the general introduction, section 1.1.1.

In all the models analyzed, the reference situation was either semi-natural woodland (Knudsen et al., 2017) or natural area before human intervention (Chaudhary and Brooks, 2018; Kuipers et al., 2021), however, as stated above extensive grazing is needed to promote grassland biodiversity and suppress forest succession (Kapfer et al., 2022; Wilson et al., 2012). Therefore, natural grassland or meadows may be a better reference situation than forest, for example, if the goal and scope of the study is to conserve natural grassland.

Another way to include ecosystem services for multi-functional systems like pasture-based livestock, would be to use the territorial LCA approach. Territorial LCAs aim to grasp all on-site and off-site endpoint impacts (damage to human health, ecosystem quality and resources) linked to the production and consumption in that territory as a whole, in order to ultimately identify the scenarios that provide the most services for each unit of impact (eco-efficiency)(Loiseau et al., 2014; Nitschelm et al., 2016). A territory would include not only a geographic dimension but also societal and economic dimensions, or as stated in Loiseau et al. (2018), “a territory can thus be described as a multifunctional system through the territorial functions that provide goods and services depending on the nature of the land and the way it is exploited (from material functions including provision of food or housing to intangible types such as landscape quality or cultural heritage)”. Therefore, these top-down models may also be useful for territorial LCAs, where larger “territories” are being studied and hotspots can be identified across many ecoregions and land use types around the world, helping identify both on- and off-site production impacts. They can also be particularly applicable to large value chain, multi-functional systems like pasture-based livestock since their value chains often have on- and off-site impacts.

We recognize that more examples and comparisons with other indicators are necessary in order to attain more certain and detailed information on the influence of a certain activity on biodiversity. There are many other indicators available in and outside LCA (Crenna et al., 2020), in addition to other top-down approaches like Lindner et al. (2019) that include parameterization of other more local factors such as fertilization, soil conservation, pest control, as well as non-LCA approaches such as pressure-state response indicators, recommended in the FAO-LEAP guidelines (FAO, 2020) for local-scale assessments.

3.6 CONCLUSION

The present study provides a first step in testing current and recommended LCIA biodiversity loss models and some suggestions for improvements. Overall, top-down approaches have been proven to be useful to conduct hotspot analysis for supply chains where many different ecoregions may be involved such as livestock and their feed. However, they may not be useful when comparing the same product at different management intensities, or comparing crop products to pasture-based livestock products. The CFs were mainly influenced by the area of the land use type rather than species or management characteristics, showing that it cannot be applied at more site-specific levels. In order to properly estimate biodiversity loss due to agricultural LU types and practices, especially for local case studies, bottom-up approaches can be more certain if CFs are available in that region. Additionally, bottom-up approaches may be more suitable for comparisons between agricultural products since the CFs for arable crops and pasture are statistically significant from each other, in addition to the fact that they are based on real field data from farmland and management practices are therefore included. These models can potentially be applied to all spatial levels and can be parameterized with different land use and management types as long as there is data available. Ultimately, the choice between approaches or the combination of the two is driven by, 1) the goal and scope of your study, 2) the data available. If only hotspot, high-level or national assessments are needed or data is available only at this level, then top-down assessments would be suitable. If the goal is to study local biodiversity loss due to agricultural land use on a particular farm or area, then bottom-up approaches would be suitable.

CHAPTER 4

LIFE CYCLE ASSESSMENT CHARACTERIZATION FACTORS FOR LAND USE IMPACTS ON BIODIVERSITY IN ORGANIC AND CONVENTIONAL FARMLAND IN THE EUROPEAN MEDITERRANEAN BIOME

This chapter has been submitted as:

Montemayor, E., Knudsen, M.T., Bonmatí, A., Antón, A. Life cycle assessment characterization factors for land use impacts on biodiversity in organic and conventional farmland in the European Mediterranean biome. Submitted to the *Journal of Cleaner Production*. Under Review.

Brief background:

As mentioned in Section 1.1.1, many Mediterranean countries in Europe like Spain, Italy, Southern France and Greece have some of the largest organic cropland areas in the EU-27, with plans to increase in the future. In addition, the Mediterranean is the most biodiverse regions in the world after the tropics. Thus, it is important to verify if organic practices can actually reduce biodiversity loss compared to conventional in the Mediterranean. Therefore, using the findings from Chapter 3, the most suitable model was chosen to develop characterisation factors for biodiversity loss due to organic crop land occupation in the Mediterranean.

4.1 ABSTRACT

Agriculture is one of the main drivers for biodiversity loss. This is especially apparent in agriculturally intensive countries such as those in Europe, with nearly half of the land occupied by farmland, causing half of all European species to become dependent on agricultural habitats. OA is seen as one possible solution due to its use of preventative and natural techniques. However, there remains much difficulty in assessing biodiversity due to its complexity, inter-dependence and high specificity on a local scale. An internationally standardized methodology called life cycle assessment (LCA) can address this complexity, but many models only approach it from a global perspective, taking into account broad land use types like cropland or pasture and broad management intensities, where organic practices cannot be distinguished from conventional ones.

Some LCA literature offer biodiversity loss characterization factors (CFs) for arable crops and pastures under organic and conventional management, via a bottom-up, field-data-driven approach. However, these studies were limited to the temperate and mixed forest biomes in Europe, and no biodiversity CFs are available for perennial organic crops nor for OA products in Mediterranean regions south of the temperate broadleaf and mixed forest biome. To fill this gap, new vascular plant biodiversity CFs were estimated for organic arable and perennial woody crops in European Mediterranean regions. It was found that the potential plant species loss on perennial woody organic cropland could not be differentiated from their conventional counterparts if the conventional system was quite extensive, but were significantly different in intensive systems. Further sub-classes of conventional perennial woody crop systems should be made. Significant differences were found between CFs for organic and conventional arable crop systems. The performance of the new CFs developed using the methodology by Knudsen et al. (2017) was tested on two crop production systems within Europe and suggestions were given regarding model improvements, including an in-depth comparison between bottom-up and top-down approaches to modelling biodiversity loss in LCA.

4.2 INTRODUCTION

The Mediterranean is the most plant biodiverse biomes in the world outside of the tropics (Cowling et al., 1996; Gerstner et al., 2017; Rundel et al., 2016), hence the importance in measuring and identifying important drivers in order to conserve its biodiversity. Additionally, the planned policy to increase OA in Europe and the rise in demand, will lead to conversions or expansions in organically managed land all over Europe including Mediterranean regions and Mediterranean crops. Thus, it is important that biodiversity loss due to organically managed land in the Mediterranean is properly assessed and compared to conventional. However, which model would be most suitable to estimate biodiversity loss due to organically managed land in the Mediterranean? As mentioned in Chapter 3, bottom-up approaches may be more reliable in terms of local, site-specific studies on biodiversity loss, for example, organic and conventional crops in European Mediterranean regions. Moreover, according to the results obtained in Chapter 3, the framework developed in Knudsen et al. (2017) is quite reliable for foreground assessments, being the only bottom-up study that describes a method to calculate CFs based on species richness measurements on cropland and pasture using standardized techniques, and is based on the ecological species-area relationship (Rosenzweig, 1995), making them inherently certain in terms of predicting species richness. The method for calculating CFs is easy to apply as long as species richness data is available on the land use type of concern. Therefore, the model by Knudsen et al. (2017) was chosen to evaluate the biodiversity loss due to land use by organically managed crops. However, these CFs are highly region-dependent, thus making the CFs based on the temperate broadleaf and mixed forest biome inapplicable to other biomes like the Mediterranean, and inapplicable to important Mediterranean crops like olives and vineyards.

Thus, CFs for the Mediterranean biome were estimated using the methods described in Knudsen et al. (2017) and secondary plant richness data from organic and conventional farms in Spain, Italy, France and Greece, for common Mediterranean perennial crops such as grapes, olives, as well as annual arable crops such as wheat. The performance of these new CFs was tested using organic crop production case studies from the Mediterranean. To the best of our knowledge, no other study has developed CFs for potential biodiversity loss due to organic and conventional land use types in the Mediterranean and their native crops.

4.3 MATERIALS AND METHODS

4.3.1 PLANT SPECIES DATA ACQUISITION

Plant species richness data for organic croplands in the Mediterranean were collected from published literature studies using Google Scholar. The keywords “organic” AND “Mediterranean” AND “farm OR agriculture” AND “plant species richness OR biodiversity” were used. This resulted in 2,770 hits. The summaries of each were checked in order to select those that provide data on plant species richness on organic and conventional cropland in the Mediterranean using the quadrat sampling method, yielding six studies and a total of 744 data points in Mediterranean countries such as Spain, Italy, Greece and Southern France. Information on crop type, sampling method and period, sample number, farm management (fertilization, pesticide use, mechanical field operations), and location (country, region, coordinates) were listed in Table 15, if reported.

In order to assess the impact of agricultural land occupation on plant species richness, data from the natural reference or baseline situation of each cropland location was required. Similar to the study by Knudsen et al. (2017), woodland forest was chosen to be the baseline land use type seeing as it would be the land use type that would arise without human influence (Koellner, 2000). Only the publication by Lüscher et al. (2016) provided plant species richness data on woodland forest present near the cropland of each farm using standardized sampling methods for Spain and France, but not for Italy. Thus, this data was used as the baseline species richness values in this study with a standardized area of 100 m^2. The plant species richness data for the baseline woodland was similar between Spain and France, and coincided with publications in other Mediterranean European countries such as Portugal (Bugalho et al., 2011; Proença et al., 2010). The type of trees in semi-natural areas were also similar between all countries and studies researched.

Table 15. Characteristics of studies used for vascular plant species richness data in organic and conventional cropland within four European countries in the Mediterranean biome.

Study	Sampling method	Sampling period	Location: Ecoregion / Country / Region	Crop type	Management type	No. samples	Mean species richness (95% C.I.) or SD	Farm management Fertilization	Herbicide applications (appl. ha-1, unless stated otherwise)	Fungicide (applications ha-1, unless stated otherwise)	Insecticide (appl. ha-1, unless stated otherwise)	No. mechanical field operations
(Lüscher et al., 2016)	One survey of 10 x 10 m quadrat in centre of selected site.	2010	Iberian sclerophyllous and semi-deciduous forests / Spain / Extremadura	Olives	ORG	14	31.33 (27.78 – 34.89	69.5±48 kg N/ha	0	0.59±0.84	0	3.99±2.28 No. /ha
					CON	14	30.67 (24.92 – 36.41)	54±38 kg N/ha	0	0.49±0.52	0	4.08±1.67 No./ha
			Northeast Spain and Southern France Mediterranean forests / France	Cereals	ORG	29	18.62 (16.42 – 20.82)	43.6±17.9 kg N/ha	0	0	0	5.38±1.16 No./ha
					CON	45	12.29 (10.44-14.14)	113.5±36.1 kg N/ha	1.72±0.99	0.55±0.6	0.23±0.34	8.16±2.22 No./ha
		2011	Italian sclerophyllous and semi-deciduous forests / Italy / Veneto	Vineyard	ORG	7	32 (26.14-37.86)	15.2±17.3 kg N/ha	0	12.31±4.18	4.73±6.35	22.14±8.66 No./ha
					CON	9	25.11 (21.41-28.81)	30.4±32.8 kg N/ha	1.84±1.50	12.93±4.20	1.51±5.60	21.02±5.60 No./ha
(Puig-Montserrat et al., 2017)	Sampled in randomly assigned quadrats of 16 m2 (8 × 2 m) in April 2013 and May 2014.	April 2013 and May 2014	Northeast Spain and Southern France Mediterranean forests / Spain / Priorat	Vineyard	ORG	22	19.86 (16.49-23.24)	No info. given	0	Sulfur: 3-4 times/year Cu: 0-2 times/y	Bt & Spinosad: 0-2 times/y (treatment prevented when sexual confusion is used) Sexual confusion: 0-1 times/y	0 – 3 times / year
					CON	20	11.70 (8.52-14.88)	No info. given	0 – 2 times/year (Glyphosate)	Sulfur: 4 times/year Cu: 0-2 times/y	Bt & Spinosad: 0-2 times/y (treatment prevented when sexual confusion is used) Sexual confusion: 0-1 times/y	0 – 3 times / year

											Chlorpyrifos & Methyl Chlorpyrifos: 0-1 Fenoxicarb & Tebufenocide: 0-1	
(Nascimbene et al., 2012)	Plants were sampled within a single 10 x 10 m2 plot placed in the centre of the cultivated area.	April 15th - May 10th, 2010	Italian sclerophyllous and semi-deciduous forests / Italy / Veneto	Vineyard	ORG	9	32 total Annual:14 (11-16) Perennial: 17 (14-22)	88±36 (50-130) kg/ha	2±1.4 (1-4) appl. / year	15.3±4.5 (9-21) appl. / year	2±2.4 (0-7) appl. / year (copper hydroxide, Bacillus thuringiensis, and pyrethroid)	2 times/year
					CON	9	25 total Annual: 13 (10-16) Perennial: 12 (10-13)	82±50 (36-160) kg/ha	0 appl./year	12.8 ± 4.2 (10–20) appl. / year	1.4±1.1 (0-3) appl. / year (Fenamidone, Mancosin, Tebufenozide)	2 times/year
(Solomou and Sfougaris, 2011)	The sampling of herbaceous vegetation was carried out in May 2007 in randomly selected plots of 0.25m2 (0.5 x 0.5 m)	May 2007	Aegean and Western Turkey sclerophyllous and mixed forests / Greece / Magnesia Prefecture	Olive groves	ORG	120	10 years after conversion: 38 Six years after conversion: 31	50 kg/tree (10 y, none for 6y) Potassium: 1-1.5 kg/tree.y Borax: 200 g/tree.y	0	No info given	No info given	No info given
					CON	180	Sprayed with herbicide: 15 Not sprayed: 25 No data on C.I. available	Calciferous nitric ammonia: 2 kg/tree.yr	Yes (no specific information given)	No info given	No info given	No info given
(Ponce et al., 2011)	A25 cm×25 cm quadrat was thrown randomly 20 times in each field, avoiding the edges and their proximities, May 2008.	May 2008	Iberian sclerophyllous and semi-deciduous forests / Spain / Madrid	Dryland cereals (wheat, barley, oat)	ORG	20	9.4±4.0 (SD)	0 kg N/ha	None (weed ploughing only)	No info given	No info given	1 – 2 times per year
					CON	20	3.4±1.8 (SD)	NPK: 350±72 kg/ha.	Weed ploughing Clorsulfuron (7%): 2–2.5 gha−1. April, May and July	No info given	No info given	2 – 4 times per year

								CAN (27%): 168±26kg /ha	Clortoluron (50%): 3–4 l ha−1 Gardel: 0.2 l ha−1 Foramsulfuron: 10gha−1. April, May and July Primafuron: 20gha−1			
(Caballero-López et al., 2010)	In each field an 80m transect was made diagonally across the centre of the field, starting at 55m from the edge. Within each transect, five 1m×1m plots at 20m intervals were surveyed.	May - June 2004	Northeast Spain and Southern France Mediterranean forests / Spain / Barcelona	Arable cereals (wheat, barley, legume) (but 60% of land dominated by woodlands)	ORG	40	8.12 (7.60-8.65)	<160 kg N/ha	Mechanical	None	None	2 – 3 times per year, 20 cm depth
					CON	40	3.05 (2.67-3.43)	~180 kg N/year pig slurry, <100 kg mineral N at times	Glyphosate, glycine at 2.5 Lha−1) and 2-4-D (2,4-dichlorophenoxyacetic at 1.3 Lha−1). Splendor 25 SC (Tralkoxidin at 1.6 Lha−1). Oxytril (ioxinil, bromoxinil, plus mecoprop at 2Lha−1)	None	None	3 times per year, 15 cm depth

4.3.2 CALCULATION OF OCCUPATION CF FOR POTENTIAL PLANT SPECIES LOSS FROM LAND USE IN THE MEDITERRANEAN

The same framework used in Knudsen et al. (2017) for estimating the impact of land occupation on plant species loss, expressed as Biodiversity Damage Potential (BDP), was used in the current study. In general, BDP can be calculated according to Eq. 1:

$$\mathrm{BDP} = \mathrm{CF} \times \mathrm{t} \times \mathrm{A} \qquad \text{(Eq. 1)}$$

where CF is the characterization factor representing the potential disappeared fraction (PDF) of plant species richness under the specific land use compared to a reference scenario, *t* is the time frame under study, and *A* is the area under the specific land use. More detailed information on how CFs were estimated can be found in Knudsen et al. (2017).

As a simplified explanation, the occupation CF expressing PDF was calculated as the relative loss in species richness, c, (Schryver and Goedkoop, 2010):

$$CF = \frac{c_{baseline} - c_i}{c_{baseline}} \qquad \text{(Eq. 2)}$$

The species richness factor c, can be estimated using the species number S in sample plot size A, and *z* is the species accumulation factor, based on the species-area relationship (Rosenzweig, 1995)

$$c = \frac{S}{A^z} \qquad \text{(Eq. 3)}$$

Combining Eq. 2 and Eq. 3, occupation CFs for every land use type were calculated within every study and for every plot, *i* or *baseline*, using Eq. 4

$$CF = 1 - \left(\frac{S_i}{S_{baseline}} \times \frac{A_{baseline}^z}{A_i^z}\right) \qquad \text{(Eq. 4)}$$

Since the sampling area varied greatly among studies, the sampled species richness (S_i) needed to be standardized to the same area. Eq.4 already does just this; it standardizes the S_i to an area of 100 m^2 by inherently incorporating the transformed power model of the species-area relationship proposed by Kier et al. (2005) and also used in Mueller et al. (2014) (Eq. 5), since the same baseline area was used across studies (100m^2).

$$S_{100m2} = S_{Sampled} \times \left(\frac{A_{100m2}}{A_{Sampled}}\right)^z \quad \text{(Eq. 5)}$$

In regards to which *z* factor to use, De Schryver and Goedkoop (2010) recommended the use of a *z* value that varies with the area occupied and type of land use, in other words a variable *z*, in order to decrease model uncertainty. However, knowledge on these two parameters is often difficult to acquire. Otherwise, the model could be simplified by using a constant *z* value of 0.25, at the cost of increasing model uncertainty due to high variation in generic *z* values reported in literature. For example, (Schryver and Goedkoop, 2010) state that under the hierarchist cultural theory perspective, the z factor and its inherent variability is responsible for more than 80% of the parameter uncertainty. However, since the land area was not always available in the selected studies, nor were *z* values available in Schryver and Goedkoop (2010) for arable or perennial crops with plot samples of less than 100 m^2 (some studies in Table 15 had plots less than this size), the constant value of 0.25 was chosen for *z* in the present study, similar to Knudsen et al. (2017). Nevertheless, the advantages of using a constant *z* value include: a more robust model that is independent of the LCI, CFs become more dependent on the difference between the $c_{baseline}$ and c_i (as opposed to land use type-independent and high sensitivity to regional effects), and can result in a higher number of significantly different CFs when using a constant z compared to a variable z (Schryver and Goedkoop, 2010). Furthermore, this constant z value is similar to those used in Koellner and Scholz (2008) to calculate CFs (z = 0.21), as well as z values for the Mediterranean forests, woodlands and scrub biome (z = 0.20, Kier et al., 2020).

When plant species richness data were available per agricultural plot of the same crop within one study, plot-level CFs were calculated and averaged to give one CF for that land use type and country. Hereafter, the crops that were studied were aggregated into two crop groups, arable and perennial crops. The first crop group included wheat, barley, oat and entomophilic and/or bee attracting annual crops, and the second crop group included vineyards and olive trees.

4.3.3 STATISTICAL ANALYSIS

Linear mixed-effects models were used to test the main effects - country, land use type (olives, vineyards, arable crops, hedges, grass strips), management (organic or conventional) and crop longevity (annual and perennial) – on corresponding CFs. A significant interaction between management and longevity would imply a differential response to management of annual versus perennial crops. The lme function implemented in the ‘’nlme’’ package using a restricted maximum likelihood estimation procedure (Pinheiro et al., 2022) in R (R Development Core Team 2008, version 2.8.0) was used. To retrieve the p-values associated with the F-values, ANOVA in the form of the function “anova-lme” (Pinheiro and Bates, 2000) was used, where a p-value < 0.05 was considered significant.

When data were available on management practices per plot in both organic and conventional fields (e.g., Lüscher et al., 2016), an independent two-sample t-test assuming unequal variances was used to check if the management practices (total average N input per ha, number of pesticide, herbicide, fungicide, insecticide applications per ha, number of mechanical field operations per ha) were significantly different between organic and conventional management per crop type. This data can be found in Table C-1. Otherwise, the average and range were used for comparison between management practices in the other studies.

4.3.4 COMPARISON WITH OTHER STUDIES

The only other recent study that had CFs for the Mediterranean biome was Chaudhary and Brooks (2018). However, this study did not have CFs for organic and conventional practices, but instead used three intensity levels, minimal, light and intense. Since minimal may correspond more closely to organic practices, and intense to conventional these levels were used in our comparisons. The only studies found that provided CFs for both organic and conventional production were Knudsen et al. (2017), Koellner and Scholz (2008), Mueller et al. (2014), De Schryver and Goedkoop (2010), and thus, were compared with the CFs in the current study. However, those studies were conducted in a different biome (Temperate Broadleaf and Mixed Forests) than the current study, and thus, absolute values could not be fully comparable, but the overall trends (if organic or conventional had higher CFs) were studied.

4.3.5 APPLICATION EXAMPLE

The applicability of the newly calculated CFs for PDF of vascular plants in Mediterranean agricultural fields was demonstrated using the same studies from which the CFs were calculated in order to compare their effects on biodiversity damage. Only Caballero-López et al. (2010) and Solomou and Sfougaris (2011) had data for crop yields, hence these were used as application examples. The characteristics of each case study are summarized in Table 16. The biodiversity damage potential caused by 1 ton of crop cultivated in either organic or conventional management practices in the Mediterranean was calculated using the different CFs developed.

Table 16. Characteristics of case studies used in the application example to calculate the Biodiversity Damage Potential per ton of crop yield.

Country	Spain	Greece
Study	Caballero-López et al., 2010	Solomou and Sfougaris, 2011
Location	Montblanquet (41◦29'0.9''N, 1◦7'16.4''E)	Western Magnesia Prefecture (39°06'54.80''N, 22°55' 16.32''E)
Crop type	Arable	Olives
Year data collected	2004	2007
Time under land use type (yr)	Org & Conv: 1 year	Org & Conv: 10 years
Mean yield (tons/ha)	Org: 2.1 Conv: 4.05	Org: 10.3±0.79 Conv: 11.4±0.2
Land area (ha)	Org: 2.19±0.3 Conv: 4.08±0.8	Org: 31.00 ±12.74[a] 29.25 ±18.64[b] Conv: 43.00 ±21.11[c] 39.25 ±20.95[d]
Mean annual Temperature (°C)	13	18.8
Precipitation (mm)	450	350.3
Soil type	unknown	metamorphic schist
Altitude (m)	627 m.a.s.l.	50 m.a.s.l.

[a] Measurements taken in farms that have been certified organic for 10 years.

[b] Measurements taken in farms that have been certified organic for 6 years.

[c] No herbicide spray applied

[d] Herbicide spray applied

The objective of this simple example was to show the comparison of land occupation biodiversity impacts due to differing management practices (organic *vs.* conventional), calculated using the new CFs from the present study.

Eq. 1 was used to calculate the BDP as a function of the CF, time, t, and area, A, under the specific land use, *i*, for each study.

To estimate potential biodiversity damage per ton of crop yield, the product from Eq. 1 was divided by corresponding crop yields in each example study ($Y_{i,study}$) for each land use type, *i*, using Eq. 6

$$BDP_{study} = \frac{CF_{study,i} \times t \times A_{study,i}}{Y_{study,i}} \qquad \text{(Eq. 6)}$$

4.4 RESULTS

4.4.1 LAND USE OCCUPATION CFS FOR PDF OF VASCULAR PLANT SPECIES

Table 17 shows the average CFs calculated for each study, by land use type and management practice (organic or conventional). Through the statistical analysis, the CFs from the Lüscher et al. (2016) dataset showed significant effects for country (Spain, Italy, France) in the common land use types hedges ($F_{2,35}$ = 12.43, p = 0.0001) and grass strips ($F_{1,35}$ = 11.91, p = 0.0015). However, there were no significant effects of management nor the interaction between management and country in these two land use types (hedges and grass strips). Significant effects were found for longevity (perennial or annual, $F_{1,124}$ = 93.52, p < 0.0001) when analyzing the CFs for all crops.

In regards to the CFs calculated for crop lines, the CFs for French arable crops showed significant effects of management ($F_{1,14}$=18.74, p = 0.0007) and the interaction between land use type (hedges, grass strips and crop lines) and management ($F_{2,132}$=5.57, p = 0.0047). Supporting these results, the CFs calculated from Caballero-López et al. (2010) for arable crops in Spain showed more pronounced significant effects of management ($F_{1,75}$=242.92, p<0.0001).

With respect to the CFs for perennial crops, the CFs for Spanish olives and Italian vineyards from Lüscher et al. (2016) data showed no significant effects of land use type (hedges, grass strips or crop lines) nor management (organic or conventional). Contradictory to these results, the CFs calculated from Puig-Montserrat et al. (2017) for Spanish vineyards did show significant effects of management ($F_{1,67}$=6.07, p=0.0163).

The studies by Nascimbene et al. (2012) for Spanish vineyards and Ponce et al. (2011) for Spanish cereals, did not have plot level data available, and thus no statistical tests could be performed. Nevertheless, both studies stated that a significant difference in vascular plant species richness was found between management practices, and plant richness was found to be influenced by the management type, vineyard or cereal cover and their interaction. Nascimbene et al. (2012) also found that the number of perennial plant species was higher in the grassland strips under ORG than CONV farming, while annual plant species richness was not affected by management. These two studies had similar CF values to the other studies with the same land use type, where Nascimbene et al., 2012 had exactly the same CFs as the Italian vineyards using (Lüscher et al., 2017) data and Ponce et al., 2011 was within the same range as the arable crop CFs in the studies by Caballero-López et al. (2010) and Lüscher et al. (2017).

The CFs calculated using data from Solomou and Sfougaris (2011) for Greek olive production did not fall within the range of the other crop land use types, but were in fact much lower, even negative, meaning the average number of plant species was higher than the baseline land use type, indicating that it had higher biodiversity quality (with the exception of conventional farms sprayed with herbicide). This may be due to the baseline species richness count used; it may be useful for Spain, France and Italy, but possibly not for Greece which could have higher species richness counts in semi-natural areas. This region in Greece has a different type of ecoregion, Aegean and Western Turkey sclerophyllous and mixed forests, compared to the other selected studies in Table 15, where they were either Mediterranean forests or semi-deciduous forests, which may also explain the difference in CFs.

Therefore, the analysis demonstrated that there was an overall effect of management (organic or conventional) in arable crop systems (CFs were highest under conventional management), but effect of management in perennial crops varied from one study to the next.

Table 17. Characterization factors (PDF/m²) for potential disappeared fraction of plant species in the different crops and management systems (organic or conventional) in four European Mediterranean countries using the LCIA framework by Knudsen et al. (2017). Mean (95% confidence interval, where sample data was available).

Study used for species richness data	Country	Land use type	CF Organic	CF Conv
Lüscher et al. (2017)	Spain	Olives	0.14 (0.04-0.24)	0.10 (-0.05-0.26)
		Lines of Tree & Scrub	0.54 (0.47-0.61)	0.47 (0.38-0.56)
	France	Arable	0.50 (0.44-0.55)	0.67 (0.62-0.72)
		Lines of Tree & Scrub	0.54 (0.47-0.61)	0.47 (0.38-0.56)
		Grass & Herbaceous strips	0.54 (0.49-0.59)	0.55 (0.47-0.63)
	Italy	Vineyards	0.13 (-0.02-0.29)	0.32 (0.22-0.42)
		Hedges	0.65 (0.23-1.07)	0.62 (0.58-0.66)
		Grass strips	0.28 (0.09-0.47)	0.47 (0.39-0.55)
Puig-Montserrat et al. (2017)	Spain	Vineyard	0.15 (0.01-0.29)	0.50 (0.46-0.64)
		Grass strips	-0.02 (-0.15-0.11)	0.30 (0.06-0.54)
Nascimbene et al. (2012)	Italy	Vineyards	0.13	0.32
Solomou and Sfougaris (2011)	Greece	Olives	-0.65[a] -0.22[b]	-0.09[c] 0.41[d]
Ponce et al. (2011)	Spain	Arable, wheat and barley	0.24	0.72
Caballero-López et al. (2010)	Spain	Arable, wheat	0.30 (0.26-0.34)	0.74 (0.71-0.77)

[a] Measurements taken in farms that have been certified organic for 10 years.

[b] Measurements taken in farms that have been certified organic for 6 years.

[c] No herbicide spray applied

[d] Herbicide spray applied

In regards to land use types in Lüscher et al. (2016), significantly higher CFs were found for lines of trees and scrub compared to olive crop lines in organically managed fields ($p<0.05$). However, there was no significant difference between these land use types in the conventionally managed fields, but this may be due to the low sample size from the lines of trees and scrub sites (n=5). For the arable farms in France, significantly higher CFs were found for arable crop lines compared to grass and herbaceous strips in CONV management (p<0.05). No significant difference was found between land use types in the ORG fields. For the vineyards in Italy, significantly higher CFs were found for grass and herbaceous strips and hedges compared to the vineyard crop lines (p<0.05) in CONV managed fields. No significant difference was found between land use types in the ORG fields.

Comparing CFs between crop systems, olive groves had lower CFs than vineyards in both ORG and CONV farms (p<0.05), and arable crops had higher CFs than both olive groves and vineyards in both ORG and CONV (p<0.05).

In regards to the CFs calculated using data from Puig-Montserrat et al. (2017), no significant difference was found between the vineyard crop lines and grass strips.

In general, the perennial crops tended to have lower CFs compared to arable crops, especially for the ORG farms, but to a lesser extent in the CONV farms studied.

4.4.2 COMPARISON WITH OTHER STUDIES

Table 18 and Table 19 show characterization factors for the land use types presented in this study compared to five other studies (Chaudhary and Brooks, 2018; Knudsen et al., 2017; Koellner and Scholz, 2008; Mueller et al., 2014; Schryver and Goedkoop, 2010). Not all land use types are represented in the other studies. In general, all studies estimated lower CFs for ORG fields compared to CONV, similar to the present study.

The organic and conventional arable crop CFs in the present study (Table 17) were similar to the studies by Koellner and Scholz (2008), Schryver and Goedkoop (2010), but higher than those in Mueller et al. (2014) (Table 18). The values are also comparable to the average values for intensive (ORG and CONV) agricultural production in Austria and Germany by Knudsen et al. (2017), but less comparable to the extensive production in Wales and, Hungary.

Only Koellner and Scholz (2008) had CFs for perennial woody crops, where their values for vineyards were higher than in the present study, whereas olive groves had similar CFs to the olives in Spain, but higher than the olives in Greece in the present study.

The CFs for hedges were much higher than in Knudsen et al. (2017), due to not only the higher baseline species richness in the present study but could also be due to the fact that some of the farms sampled in their study were managed quite extensively. However, direct comparisons cannot be made regarding specific management practices between farms in the present study and Knudsen et al. (2017) since information regarding this was not available in their study.

On the contrary, these CFs (as well as all the other CFs from the other studies) were much higher than the studies by Chaudhary and Brooks (2018), lying well outside their range (Table 19). Specifically, they were lower by an order of negative nine. This is mainly due to the inherent difference in modelling the PDF damage potential; Chaudhary and Brooks (2018) is a model for high-level ecoregion scale assessments, whereas the method used in the present study is useful for regional or site-level assessments. What caused the CFs in Chaudhary and Brooks (2018) to be much lower mathematically, is how they calculated their regional land occupation CFs, they multiplied an allocation factor by the projected species loss for a specific species in that ecoregion, divided by the area of that land use type in that ecoregion. The allocation factor (denoted as $a_{i,j}$ in their study, where i is the land use type and j is the ecoregion) represents the area share of a specific land use type (e.g., cropland) within a specific ecoregion (e.g., Northeast Spain and Southern France Mediterranean forest). Since the area of any land use type compared to the total area of an ecoregion would always be extremely small (even compared to the other variables that the CF depends on such as taxon affinity or management intensity), the final allocation factors $a_{i,j}$ would also be extremely small. This is the main reason why the CFs in Chaudhary and Brooks (2018) were consistently low on orders between -6 and -18. For example, in ecoregion AA0103, the area share of pasture would be 2.75×10^{-8}, leading to a regional land occupation CF for amphibians of 4.56×10^{-10}. Therefore, the CFs in Chaudhary and Brooks (2018) rely much too heavily on the area share of a specific land use type, and not enough on taxon affinity or management intensity.

Table 18. Average characterization factors (PDF/m^2) for potential disappeared fraction of plant species in other studies. The studies that did not have available CFs for that land use type are represented with a hyphen (-).

Land use type		Knudsen et al. (2017)	Schryver and Goedkoop (2010)	Mueller et al. (2014)	Koellner and Scholz (2008)
Arable crops	Organic	0.29[a]	0.36	0.15	0.36
	Conv.	0.68[a]	0.79	0.60	0.74
Vineyards	Organic	-	-	-	0.42
	Conv.	-	-	-	0.57
Orchards/Groves	Organic	-	-	-	0.10
	Conv.	-	-	-	0.13
Hedges	Organic	-0.15	-	-	-
	Conv.	-0.02	-	-	-

[a] Values based on Austria and Germany in Knudsen et al. (2017).

Table 19. Global land occupation characterization factors (97.5% confidence interval values) for plants on cropland per ecoregion and intensity type from Chaudhary and Brooks (2018).

Ecoregion	CF for cropland as potential species loss/m² per intensity type		
	Minimal	Light	Intensive
Mediterranean woodlands and forests	5.76E-11	6.15E-11	6.15E-11
Northeastern Spain & Southern France Mediterranean forests	5.72E-10	6.11E-10	6.12E-10
Southwest Iberian Mediterranean sclerophyllous and mixed forests	6.52E-10	6.96E-10	6.97E-10
Aegean & Western Turkey sclerophyllous and mixed forests	3.61E-10	3.85E-10	3.86E-10

4.4.3 APPLICATION EXAMPLE

Using the yield data provided in the species richness studies used to calculate the CFs in the present study (Table 16), the biodiversity damage (BDP) potential was calculated for each respective study and management type using Eq. 6, shown in Figure 17 below. Not all studies provided yield data, thus the BDP was calculated only for those that did (Greek olives and Spanish cereals).

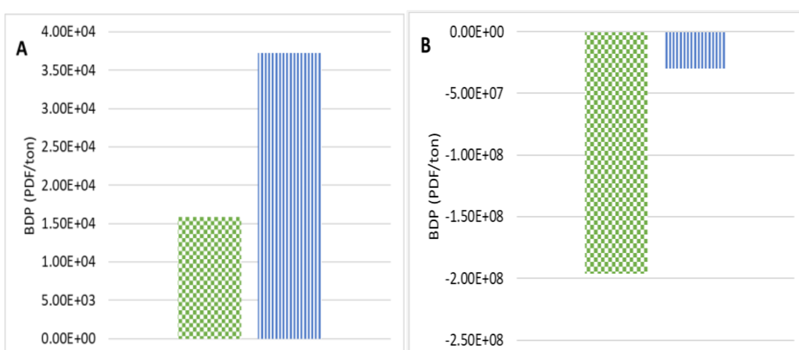


Figure 17. Biodiversity damage potential for ORG (checker green) and CONV (blue lines) A) Spanish arable crops and B) Greek Olives using data from (Caballero-López et al., 2010; Solomou and Sfougaris, 2011), respectively. The ORG data from Solomou and Sfougaris, 2011 were from ORG farms 10 years after conversion and the CONV data were from farms sprayed with herbicide.

The arable crops in Spain had lower BDP per ton in organic compared to conventional farms using data from (Caballero-López et al., 2010), despite CONV having higher yield. The same was found for the olive production in Greece, the CONV production had higher yield, but the BDP was still lower for ORG practices (Figure 17), showing both were more dependent on the CF than on yield.

Therefore, this simple example shows that the new CFs calculated from Caballero-López et al. (2010) and Solomou and Sfougaris (2011) were able to distinguish between the impact caused by different management practices in perennial crops in the European Mediterranean region.

4.5 DISCUSSION

4.5.1 MANAGEMENT PRACTICE

To explain why there was no significant difference between the ORG and CONV CFs for perennial crops (Spanish olives and Italian vineyards) in the Luscher et al. (2016) data, the specific management practices were analyzed (Table D-1 in the Appendix). It was found that the CONV farms in both crops were quite extensively managed, with no significant difference between ORG and CONV farms in terms of fungicide and herbicide application, total N input and ploughing ($p<0.05$). The exception was herbicide application in Italian vineyards, where a significant difference in herbicide applications per ha was found between the ORG and CONV. However, the CONV farms that applied 0 or 1 applications per ha (compared to 2-4 applications per ha in the other CONV farms) had the lowest CFs, hence lowering the overall mean for the CONV Italian vineyard CF.

Additionally, many of the ORG (11/13) and CONV (13/18) olive farms in Luscher et al. (2016) were already covered with herbaceous vegetation or mid-phanerophytes as opposed to bare ground, thus adding to the fact that the CONV management was quite extensive.

On the contrary, the CONV management practices in Nascimbene et al. (2012) and Puig-Montserrat et al. (2017) were quite intensive compared to ORG farms, where chemical herbicides were added in CONV 2±1.4 glyphosate appl. per year and 0-2 times/yr in each study, respectively, compared to zero appl. per year in ORG (Table 15). Solomou and Sfougaris (2011) also used herbicides in CONV farms but no specific quantity or type was mentioned. The ORG farms in these three studies did not add any herbicide, opting only for mechanical weeding, sheep grazing or no treatment at all (Table 15). This explains the significant difference between ORG and CONV plant species richness within the studies themselves and in the CFs found in the results.

Thus, for the application of the new CFs, it is recommended that the practitioner find out if CONV practices (e.g., herbicide application, tillage, etc.) in perennial crops in the Mediterranean are significantly different from ORG, and if so, one can use CFs from Nascimbene et al. (2012), Puig-Montserrat et al. (2017), and Solomou and Sfougaris (2011). However, if the practices are similar (meaning CONV regimes are quite extensive), then CFs derived from the (Lüscher et al., 2016) study could be used.

Additionally, the oversimplification of management practices into binary variables (ORG and CONV) and their interaction with continuous CF measures could have underestimated the effects of farming practices in perennial crops. The CFs may be more useful for perennial crops if non-binary variables were used to account for more levels of intensity. For example, in (Solomou and Sfougaris, 2011) they differentiated between CONV olives sprayed with herbicide and CONV not sprayed with herbicide, resulting in significantly different plant species richness. Additionally, tillage intensity has also been found to be an important factor for plant species richness in both perennial forage and annual crops (Martin et al., 2020) as well as in woody crops (Rey et al., 2019). Thus, till or no-till could be further land use sub-classes to include. Overall, the CFs developed in Table 17 are recommended for use in the Mediterranean, since they are based on real field measurements of multiple farms throughout the biome, and if the goal of a study is to look at the potential plant species loss for these crops at high-level across the Mediterranean, an average may be taken. However, it must be transparently reported the aforementioned points regarding differences in intensity where sometimes organic may be similar to conventional if the conventional practices are extensive.

In terms of other indices for biodiversity management analyzed in the studies in Table 15, Puig-Montserrat et al. (2017) found that vegetation density was higher in ORG vineyards than CONV, where greater differences were found in grass strips compared to crop lines. In Italian vineyards, (Nascimbene et al., 2012) found that overall species composition did not differ between ORG and CONV practices, and plant assemblages were also similar. In the olive groves in Greece, Solomou and Sfougaris (2011) found that beta diversity of herbaceous and woody plant species and density and cover of woody plants tended to be higher in ORG (after 10 years of conversion) compared to CONV. For arable crops in Spain, not only was weed richness higher in ORG compared to CONV, but also plant cover and abundance (Caballer-Lopez et al., 2010; Ponce et al., 2011). Ponce et al. (2011) found that the differences between ORG and CONV weed species richness found in their study were higher than those in northern latitudes, due to the overall richer weed flora in the Mediterranean region, and higher weed seed availability due to the 2-year rotation system typical practiced in Iberian dry cereal farmland.

Another trend worth mentioning is that the number of years after conversion to organic has been found to affect plant species richness in perennial crop fields, where richness was significantly higher after 10 years of conversion to organic olive groves compared to six years (Solomou and Sfougaris, 2011), hence, affecting the CFs calculated from this data. This demonstrates that the number of years after conversion may be an important factor to consider when analyzing PDF in organic fields, and would require more research. Additionally, as mentioned in section 1.1.1, the yields of organic food products approach those of conventional ones as the time after conversion increases. Therefore, the increase in plant species richness compounded with the smaller yield gap between organic and conventional as time after conversion passes, could reduce the BDP of organic products even further.

4.5.2 COMPARISON WITH OTHER APPROACHES

In general, though the method used in the present study (based on Knudsen et al., 2017) was derived from the classic species-area-relationship (SAR) model ($S=cA^z$), it still addresses important gaps in the classic model. These gaps include i) its inability to capture biodiversity change, ii) that it can over/underestimate results, iii) assumes that all natural areas converted to human-dominated areas become completely hostile to biodiversity, iv) it does not account for taxon affinity to land use types, and v) it does not account for habitat heterogeneity or vi) land use intensity. The method in Knudsen et al. (2017) addresses gap *i* by calculating species loss relative to semi-natural areas. Moreover, the classic-SAR model was found to be suitable and useful in the present study since real field measurements were used to estimate CFs for potential disappeared fraction of plants in organic and conventional fields, thus little inference is made regarding the actual PDF in the land use types assessed. Due to this bottom-up approach, the model in Knudsen et al. (2017) inherently addresses points *ii, iii* and *iv*, where these assumptions now become fact; the results are an actual reflection of real biodiversity measurements and not an over- or underestimation, and in the majority of the cases studied here, agriculture was hostile to biodiversity and plants had an affinity to grow in organic fields in general. Finally, it is able to account for gap vi) land use intensity, in the form of organic compared to conventional practices, as well as extensively or intensively managed conventional fields. However, the Knudsen et al. (2017) model cannot address gap v) landscape heterogeneity, which is further discussed in Section 4.5.5.

A general intrinsic issue with top-down approaches such as in Chaudhary & Brooks (2018) is that the model always needs to be validated by real biodiversity data, whereas, bottom-up approaches such as that taken in Knudsen et al. (2017) is already bottom-up, thus inherently validated for those specific regions. In the case of Chaudhary & Brooks (2018), they model extinction predictions which needs to be validated against real data, and its performance evaluated using different goodness fit metrics. Additionally, agricultural land use types are aggregated into broad classes, cropland and pasture. This is the proportion of the total area of cropland or pasture in a particular ecoregion, thus is a mixture of many types of crops, e.g., vegetables, perennial and arable crops, and different pastures, e.g., monocots and mixed. However, according to our results, some organic CFs for biodiversity loss can be significantly different or similar to conventional CFs depending on the type of crop (arable or perennial). This would need to be disaggregated into crop groups in order to attain more robust CFs for different management systems such as organic and conventional agriculture. A previous version of the model (Chaudhary et al., 2015) did include further land use classes (e.g., annual, perennial, organic farms, etc.) by translating country-level proportions of annual and perennial crops to ecoregion level. However, this upscaling can introduce further unknown amounts of uncertainty, thus the updated model (Chaudhary and Brooks, 2018) opted to use broader intensity classes that were based on direct, unscaled data. Chaudhary and Brooks (2018) state that future studies should include further land use classes, but new high-resolution, harmonized and validated land use maps with different intensity types are needed. Field management practices are aggregated into three intensity levels, minimal, light and intense use per ecoregion. They state that organic farms in developed countries as well as high-intensity farms in developing countries would often fall under the light intensity category. However, the light intensity category may include the addition of mineral fertilizers and synthetic pesticide application, which is not authorized in the EU organic regulations, and which are important parameters that could affect plant species richness and subsequent under-estimation of CFs. Again, it must be noted that the model by Chaudhary and Brooks (2018) was meant to be used for global, high-level assessments, and should be used as so, and site-level assessments should use models such as in the present study or those in Table 18.

In relation to plant species loss, the Chaudhary and Brooks (2018) model did not calculate taxon affinity to specific land use intensity types (referred to as variable *h* in their study) due to a lack of data for all plant species in the IUCN Habitat Classification Scheme (International Union for Conservation of Nature, 2015). Instead only the fractional relative richness from Newbold et al. (2015) was used as a proxy, which was based on a limited number of field studies, hence adding more uncertainty to this variable.

Another limitation relevant to management practices was that the fractional relative richness factors (referred to as variable f_{RR}) were taxa and region generic. This means that this variable did not take into account the sensitivity of one taxon to different intensity levels, and the authors mention that this may be the reason why the CFs calculated in their study do not differ much across the three intensity levels.

Therefore, top-down approaches are useful for global metrics, showing high-level trends, whereas, bottom-up approaches are useful for field-level metrics.

If a mix of the two approaches were to be made, the Chaudhary and Brooks (2018) model could be adapted to include organic and further crop land use types, where the most important variables that would need to be recalculated include:

- $p_{i,j}^{intensity}$ (Proportion of total broad land use area under a particular intensity level (minimal, light or intense use). To adapt this to the proportion of total arable or perennial cropland area under organic or conventional management, FiBL, the Swiss Research Institute of Organic Agriculture, or FAOSTAT (https://www.fao.org/faostat/en/) could provide such data.
- f-RR (fractional relative richness, the local species richness in a specific land use type and intensity divided by the average local species richness in the corresponding broad land use type): studies such as the ones used in the present study could be used (Table 15), especially Lüscher et al. (2016) which collected data across 13 European countries using standardized measurement methods. However, further research and data would be needed to apply this to other regions outside of Europe.

The study proposed by Lindner et al. (2019) provides a biodiversity LCIA framework that can differentiate between specific management practices in more detail and could contribute to defining intensity levels more accurately. However, it is a top-down method that generalizes biodiversity loss and the biodiversity variable they estimate is not inherently testable, meaning the values they calculate cannot be proved with on-field measurements. Testing was planned for this method in this thesis, however, the data requirements are very high (14 metrics from diversity of weeds, structures, and soil conservation measures, material and PPP inputs), or the metric/units were not very clear or well explained (e.g., existence of rarer species in units of %time, crop rotation in units of points). Also, it was not clear to me how some variables in their study were calculated, for example, how they decide on the hemeroby levels (LU max, LU min), i.e. which ranges should be used for which LU types, and how Q_{min} and Q_{max} are calculated calculated, and when to use the “AND” operation (equation 2 in their work) or the “OR” operation (equation 3) when calculating z(y). More guidance would be helpful in the application of this model.

4.5.3 BASELINE SITUATION

In general, the Mediterranean biome has the highest plant species richness in the world outside of the tropics, being higher than temperate regions (Cowling et al., 1996; Gerstner et al., 2017; Rundel et al., 2016). Furthermore, negative biodiversity responses to land use change were found to be strongest in tropical and Mediterranean biomes globally, where the average reduction in species richness for harvested croplands (woody plantations and herbaceous croplands) compared to primary vegetation, were between 20 and 40% (Newbold et al., 2020). This study also found that species richness loss increases with greater human disturbance, which is therefore particularly applicable to the EU-27 where humans continue to dominate the land with over 47% (EC, 2007a) used as arable or pastoral farming. This would account for the higher species richness found in the baseline scenario in the present study compared to the other LCA studies that calculated CFs for ORG and CONV farms (Knudsen et al., 2017; Mueller et al., 2014; Schryver and Goedkoop, 2010). Thus, it is especially important to monitor and provide estimates for biodiversity change in the Mediterranean given its ecological importance and sensitivity to land use change, in which the present study intended to address and provide insight into what types of land use may lower biodiversity damage.

4.5.4 CROP TYPE

In general, it was found that perennial crops had lower CFs than arable crops, which is substantiated in Martin et al. (2020), where higher biodiversity was found in perennial crops compared to annual, however, more pronounced if perennial crops were untilled and annual crops tilled. This is likely due to the fact that perennial crops, such as olives and vineyards are subject to lower levels and lower need of disturbance and is more stable over time than annual crops (Asbjornsen et al., 2014). Perhaps this may change for fruit trees if they are cultivated more intensively. Nevertheless, perennialization, the practice of incorporating small amounts of perennial vegetation in strategic locations within fields dominated by annual crops, is a recommended practice that can increase a wide variety of ecosystem services, such as biodiversity, hydrologic services, pollination, control of pests, prevent erosion, and provide a wide variety of food and fuel (Asbjornsen et al., 2014). However, it must be kept in mind that a monoculture of perennial or perennial crops can have a larger detrimental effect compared to diverse mixtures of perennial species interplanted with other crops or cover, as the latter offers more habitat types for predators that attack pests. Thus, although perennial crops may have lower PDF of plant species compared to arable, it could be improved by making the cropland more ecologically diverse.

4.5.5 LIMITATIONS

Since the data used in the present study was so localized, the uncertainty of the CFs increases when extrapolated to larger scales, like the Mediterranean biome. This is similar to the uncertainty in CFs for top-down approaches when applied to local situations. Thus, the CFs estimated in the present study should be carefully used, and applied up to the ecoregion level (ecoregions given in Table 15), but in the future more data would be needed to be able to apply CFs at biome level with higher certainty.

The CFs used in the present study were created using a constant z value, and because there is high uncertainty associated with constant z values due to high variability (between 0.12 and 1.00), the CFs should only be used for relative or comparative studies, and not be used as absolute values and in weighting or normalizing steps. This was recommended by Schryver and Goedkoop (2010) in their article analyzing the uncertainties in choosing different z values on biodiversity assessments.

Unlike in Knudsen et al. (2017), data used in the present study was not gathered via a standardized sampling method, rather it was based on secondary data from different studies, using different techniques. However, the data from Lüscher et al. (2016) were all gathered using the same standardized sampling method as in Knudsen et al. (2017). The data from Lüscher et al. (2016) is quite valuable in this aspect, as well as having data for many other countries and regions other than the Mediterranean and Temperate Broadleaf and Mixed Forest biome (studied in Knudsen et al., 2017). Therefore, more CFs may be calculated using their dataset and the bottom-up method proposed by Knudsen et al. (2017) and since biodiversity is becoming a more popular and pertinent issue, more data will become available in the future. Nevertheless, the meta-study by Tuck et al. (2014) found that ORG increases biodiversity by ~30% compared to CONV, and this was consistent even across sampling scales.

Another limitation associated with the CFs developed in this study, as well as the other LCA studies that also developed PDF CFs (listed in Table 18) is that the complexity and diversity of the ecological structures in the landscape, or in other words, landscape heterogeneity was not accounted for. Farmland heterogeneity can have similar or larger effects on field biodiversity than management practices used in the crop fields (Martin et al., 2020). For example, structures like hedges can increase local plant, pollinator and bird biodiversity (Hole et al., 2005; Puig-Montserrat et al., 2017; Rey et al., 2019; Vickery et al., 2009), and play an important role in protection of natural predators of pests. Specifically for olive groves in Spain, plant species richness was higher in extensive compared to intensive management and increased with landscape complexity in both types of management. In fact, no saturation point was found for plant species richness as landscape complexity increased, as it can support more plant niches (Rey et al., 2019). Therefore, intensively managed olive groves in simple landscapes suffer a more significant loss of biodiversity compared to complex landscapes, consistently across different groups of organisms. This is particularly relevant to Spain, where the current Common Agricultural Policy (CAP) assumes that woody croplands like olive groves are inherently semi-natural, thus requirements to achieve biodiverse landscapes in this type of cultivation are quite relaxed, which is evidently inadequate in terms of biodiversity (Rey et al., 2019). These authors also found that ORG olive cultivation in Spain is often of lower productivity within complex landscapes, and infrequently found in highly productive systems within simple and intermediate landscapes, where the latter could enhance biodiversity more efficiently. Thus, more data would be needed with plant species richness measurements in farms with varying landscape complexity (e.g., simple, intermediate, complex), to create CFs that can differentiate between levels of heterogeneity. An example of a model that does account for habitat heterogeneity is Kuipers et al. (2021), but as mentioned previously in Chapter 3, this is only done from the top-down.

The authors of the present study recognize that current methods in LCA, including the methods used here, are based on indicators that reflect changes in compositional aspects of biodiversity, namely species richness. However, biodiversity is also physical organization of elements and ecological and evolutionary process acting among elements (i.e., functional biodiversity). Thus, further research (and data) is needed to include these other aspects of biodiversity in the framework.

Finally, the present study used plants as a proxy for biodiversity, as they create and shape terrestrial ecosystems and its diversity correlates highly with other species groups' diversity (Duelli and Obrist, 1998). Specifically, arthropod richness and abundance was higher in ORG compared to CONV arable crop fields due to the higher plant species richness in ORG fields (Caballero-López et al., 2010; Ponce et al., 2011). Moreover, plants and other less mobile taxa are most affected by ORG practices as they are strictly reliant on soil or plant conditions, compared to highly mobile taxa like birds (Puig-Montserrat et al., 2017). However, we recognize that many other less mobile taxa, such as invertebrates and arthropods, should be considered and new CFs should be made for these taxa in the future.

4.6 CONCLUSION

The impact of ORG compared to CONV farming on local plant biodiversity in the Mediterranean can be differentiated in arable crops, but could not be differentiated in perennial crops such as olive and vineyard, based on the available studies, since they were highly dependent on intensity of management practices, despite if the farm was ORG or CONV. Further research is needed to create more land use sub-classes for woody perennial crops to account for other important drivers such as herbicide application levels and tillage intensity, especially in CONV, as well as landscape heterogeneity in both ORG and CONV. Nevertheless, CFs derived, bottom-up, from real field measurements of species richness ensures higher certainty of the results, thus this method would be recommended for use to develop new CFs for those land use types lacking CFs. Though this may be data intensive, more and more data on biodiversity is becoming available, so in the future, development of more CFs is viable, even with further land use sub-classes.

CHAPTER 5

MAIN CONCLUSIONS OF THE THESIS

5.1 GENERAL CONCLUSIONS

This thesis highlights some methodological issues in LCA, specifically in application to organic agricultural production systems. For example, when carrying out a LCA of organic products, the typical issues usually come to light, where the impacts are very high compared to conventional using product-based functional units, and the reverse using land-based functional units. However, I found through my PhD research that the picture is not so black-and-white, due to methodological limitations of LCA. There is a grave lack of data or high variation of data in general regarding inputs used for organic products. In addition, datasets for important inputs like plant protection products and organic fertilizers, and their associated emission outputs are deficient. Not accounting for these in LCA shows that the inventories may not be fully representative. In addition, biodiversity indicators are not often reported in many LCAs of organic products as there is no consensus on which model to use, and the currently recommended models have not been tested or no clear guidance has been given on their use. Properly including ecosystem services like biodiversity may help decrease the "yield gap" between organic and conventional agriculture (refer to section 1.1.1), since it would help paint a larger picture of impacts. Therefore, returning to the initial research question, "*how can LCA been improved in order to accurately and comprehensively account for the environmental impact of organic agricultural systems?"* (Section 1.3) I believe this thesis provides a first step in improving LCA through the improvement of LCIs for organic crops, provides guidance on LCIA biodiversity model use and provision of new CFs for organic crops in the Mediterranean.

More specifically, the following sections describe how the original objectives of the thesis (Section 1.3) were achieved, by organizing them into three main sections based on chapters 2, 3 and 4:

1. Critical analysis of state-of-the-art organic crop LCI datasets, analyzing the gaps and suggesting improvements.
2. Enhancing life cycle impact assessment methodology for biodiversity assessments due to agricultural land use.
3. Develop characterization factors for organic and conventional agricultural land use types in the European Mediterranean biome using bottom-up modelling techniques.

Furthermore, general future research ideas that came out as a result of this these are found in the last section 5.5.

5.2 CRITICAL ANALYSIS OF STATE-OF-THE-ART ORGANIC CROP LCI DATASETS, ANALYZING THE GAPS AND SUGGESTING IMPROVEMENTS.

Objective 1a: What are the challenges in state-of-the-art life cycle inventory modelling of organic food products?

- Unrepresentative plant protection product manufacturing and organic fertilizer treatment inventories in ecoinvent and AGRIBALYSE® databases were found to be the principal limitations in the LCIs of organic crop products. This was due to the use of unrepresentative proxies, lack of available usage statistics or were excluded from the study all together. Use of unrepresentative proxies like mineral fertilizers or synthetic pesticides can contribute between 4 – 78% to resource and energy-related impact categories.
- It was found that emissions from fertilizer and plant protection product application were modelled using simplified modelling assumptions, such as the exclusion of application technique (e.g., injection or broadspray) when modelling ammonia emissions to air.
- These crucial aspects can be transferred to respective LCAs that use these LCI datasets, thus, this chapter informs practitioners of these significant limitations.

Objective 1b: How can LCI modelling be improved?

- New manufacturing LCIs were provided for some widely used plant protection products in organic farming (e.g., Bacillus thuringiensis, chitosan, Spinosad), as well as recommendations for fertilizer treatment LCIs and more accurate emission models.

5.2.1 FURTHER RESEARCH

- Many manufacturing LCIs are still required for other natural plant protection products used in OA, such as mineral oil, predatory insects like *Nesidiocoris tenuis*, plant oil extracts like Re*ynoutria sachalinensis* or oregano.
- The fate of application emissions of biological control agents and other natural PPPs need further research.

- A consensus must be made on how manure is allocated between livestock farm and field application, especially when it is converted into a valuable product.
- More regional LCIs for organic residue treatment need to be developed for more certain LCAs for OA.

5.3 ENHANCING LIFE CYCLE IMPACT ASSESSMENT METHODOLOGY FOR BIODIVERSITY ASSESSMENTS DUE TO AGRICULTURAL LAND USE.

Objective 2a: What are the challenges and strengths of currently recommended LCIA biodiversity loss models for evaluating the environmental impact of food products like livestock products?

- The top-down approaches were influenced more by the area of the land use type than the species affinity or management practices for example, therefore, seems that it is more important saving land area than changing land use practices. Nevertheless, if we are to transition towards sustainable agricultural practices, we should use models that are able to estimate the impacts due to practices, and not broad land use types within an ecoregion.
- Bottom-up models rely on good quality and quantity of data, with it being very data intensive. More often than not, not enough data is available to use these models to yield sufficiently reliable CFs.

Objective 2b: How can currently recommended LCIA biodiversity loss models be used in different spatial modelling contexts, like top-down and bottom-up scaling approaches?

- Top-down approaches are useful for global value chains such as livestock production, due to their global-based data and characterization factors (CFs) on ecoregion level. These are useful if the goal and scope of the study is a general hotspot analysis of both the value chain and species type, however, should not be applied at local or farm level, as the uncertainty would greatly increase. The CFs are based on extinction predictions; thus, biodiversity loss is inferred.
- Bottom-up approaches may be more suitable for comparisons between agricultural practices since the CFs for arable crops and pasture are statistically significant from each other, in addition to the fact that they are based on real field data from farmland and management practices are included. However, more data is needed to apply this to many spatial scales due to its high site-specificity.

5.3.1 FURTHER RESEARCH

Objective 2c: What further research is required to improve these models?

- The study by Kuipers et al. (2021) would benefit by integrating management practices into the CFs, as well as CFs for plants as this taxon is often the most affected. These would make this model much more well-rounded and results would be able to be compared more precisely to Chaudhary and Brooks (2018).
- Site-specificity needs to be improved for both top-down models, Chaudhary and Brooks (2018) and Kuipers et al. (2021), especially because they could not differentiate well between cropland and pasture CFs.
- More investment in data collection must be made if more certain assessments via bottom-up approaches are to be made, such as automatic species identification using machine learning.
- Other pressures on biodiversity loss besides land use should be integrated into LCIA such as climate change, invasive and non-native species, pollution, use of water bodies, direct exploitation of organisms, and indirect pressures such as people's disconnect with nature and lack of value and importance of nature.
- Instead of semi-natural forests, different reference states should be used for pasture land use types such as natural grassland or meadows since extensive grazing is needed to promote grassland biodiversity and suppress forest succession.
- Specifically for livestock products, the system is multi-functional especially for organically managed systems where they may function to supply ecosystem services such as food production, conservation/ecological intrinsic value, and cultural and financial functions. These are often not included in LCA, and should be embedded somehow, where some suggestions were given.
- This may be a useful tool for the land-sparing/land-sharing debate, where more research can be done to include landscape complexity and interconnectivity between natural "spared land" and agricultural land (found to be complementary to conserving biodiversity, discussed in the introduction section 1.2.2) , whereas as the model stands, only fragmentation is assessed rather than interconnectivity of landscapes.

5.4 DEVELOP CHARACTERIZATION FACTORS FOR ORGANIC AND CONVENTIONAL AGRICULTURAL LAND USE TYPES IN THE EUROPEAN MEDITERRANEAN BIOME USING BOTTOM-UP MODELLING TECHNIQUES.

Objective 3a: Using the findings from objective 2 above, what bottom-up model would be most suitable to develop characterization factors for organic and conventional agricultural land use types?

- The model by Knudsen et al. (2017) was chosen as it is based on the ecological relationship, the species-area-relationship, was easy to use practically (not very data intensive), inherently includes management practice effects as two different practices were tested (ORG vs CONV) and are based on field measurements of species richness. This ensures higher certainty of the results, where no validity tests need to be done. However, these CFs are quite localized and care must be taken if applying them to a higher geographic scale. Another limitation is that it does not account for habitat fragmentation unlike the SHR in Kuipers et al. (2021) or heterogeneity.

Objective 3b: What is the potential species loss of organisms due to organic and conventional agricultural land use types for European Mediterranean crops like olives, vineyards and cereals?

- The developed characterization factors (CFs) for organic arable crops were significantly lower than conventional arable crops in all countries studied.
- Some of the CFs for perennial crops, however, could not be distinguished between organic and conventional practices, unless these practices were further subdivided into subclasses of organic intensive/extensive and conventional intensive/extensive, due to the conventional practices being quite extensive in general. The CFs for organic extensive perennial crops could not be differentiated from conventional extensive, whereas, organic intensive could be differentiated from conventional intensive. From this, also comes the idea that the issue may lie in defining what "conventional" agriculture is, should "extensive conventional" be categorized with organic since PSL values are very similar, even though it is not actually certified organic? This would require more research into the other impact categories to see if there is no significant difference between them as well. Thus, better terminology that could be used is organic compared to "non-organic" since organic systems have very clear regulations in place.
- Using two case studies, one for arable crops in Spain and one for olives in Greece, organic crops had lower biodiversity damage potential than conventional in both case studies, despite the conventional

farms having higher yield. This shows that the CFs had a greater influence on the impact than the yield.

5.4.1 FURTHER RESEARCH

Objective 3c: What further research is required to improve this model?

- More biodiversity data must be collected for this model to be used and applied to other countries and scales due to its high site-specificity. The data collection techniques should be standardized to increase consistency and comparability. Automatic biodiversity monitoring would aid the collection of data such as machine learning for species identification.
- Integrate critically threatened or common species into the framework, so that the BDP could be distinguished among land use types that have similar species numbers but different number of threatened species.
- Research into how to include landscape complexity such as fragmentation in the model, such as including further land use subclasses like organic, extensive, complex/simple/mixed.
- CFs for pasture in different Mediterranean ecoregions also need to be developed using bottom-up approaches like Knudsen et al. (2017).
- Develop more CFs for different taxon using this model, especially those that have a high affinity for agricultural land use types and that are highly affected by agricultural practices, such as invertebrates and arthropods.

5.5 GENERAL FUTURE RESEARCH IDEAS

The main research question posed can be quite broad, and through my PhD research, many other limitations that could not be addressed came to light. Thus, here I will discuss other important future research ideas, on *how LCA can be improved in order to accurately and comprehensively account for the environmental impact of organic agricultural systems?*

One of the other pressures that contribute to biodiversity loss is pollution, due to the toxicity effects it has on organisms exposed to it. The principal model used for toxicity impacts in LCA is the USETox^{TM} model (Rosenbaum et al. (2008), https://usetox.org/), specifically for freshwater ecotoxicity and human toxicity. Since the main differences between organic and “non-organic” systems are the use of synthetic pesticides and fertilizers, it would be important to explore toxicity effects of these in the future. Initially, work was planned to research this, especially in developing new characterization factors for plant protection products that have missing CFs. For example, in the project Operationalising Life Cycle Assessment of Pesticides (OLCA-Pest) with the Danish Technical University (https://www.sustainability.man.dtu.dk/english/research/qsa/research/research-projects/olca-pest), it was planned to assess many PPPs used in OA such as plant-derived essential oils, or biological pest controls in the Deliverable 2.2, of which I am co-author (https://www.sustainability.man.dtu.dk/english/research/qsa/research/research-projects/-/media/2B43946E542C49EEB3F8E6B20753034E.ashx).

Similar to this, LCA focuses only on one pressure that causes biodiversity loss, land use. It does not include the other pressures such as invasive species and non-native species, climate changes associated with global warming, and overexploitation (extreme hunting and fishing pressure). The taskforce Global Life Cycle Impact Assessment Method (GLAM, https://www.lifecycleinitiative.org/category/glam/) are currently working on integrating climate change pressures into biodiversity loss models, but further work is still needed on invasive and non-native species as well as over exploitation.

Another important aspect that is extremely important to consider is the critical analysis of organic livestock inventory and how to include various ecosystem services into the LCA. Main differences between organic and “non-organic” livestock systems is the space and quality of the space given to the animals (higher ha per animal, and must be clean and have access to outdoors), the use of antibiotics, general welfare is also taken into account, among many others mentioned in Chapter 3. It would be interesting to see if/how these are modelled and how they may contribute to the LCA results. Currently, pharmaceutical products such as hormones and antibiotics, veterinary treatment and artificial insemination are not included in the LCI of many databases like AGRIBALYSE and ecoinvent, either due to no available secondary datasets for the pharmaceutical products and/or there are no LCIA methods to manage the impacts of the flow, which has been found to be one of the major gaps in the LCA of PhACs (Emara et al., 2019). This is one of the main differences between OA and CA, where the use of PhACs is limited to treatment and limited in quantity in OA, whereas in CA it is used for control, prevention and treatment, and sometimes as growth promoters. The livestock sector is estimated to account for 70-80% of total PhAC consumption worldwide (calculated from (Boeckel et al., 2017; Walpole et al., 2012), demonstrating its significance. Life cycle inventories for production and impact pathways for emissions should be included as their highly specialized production can be associated with higher energy consumption and related impacts from synthesis processes than other chemicals (Wernet et al., 2010) and their emission could have impacts on the environment and human health, having been found in waterways (Arikan et al., 2008; Daghrir and Drogui, 2013), and as residues left in meat products, causing anti-microbial resistance in the environmental and in humans as well as allergic reactions (Almashhadany et al., 2022; Manyi-Loh et al., 2018; O'Niell, 2016).

Life cycle inventories have been created for select pharmaceutical products (Cespi et al., 2015; De Soete et al., 2014) and can serve as a guide on how to build more LCIs. A review on state-of-the-art PhAC inventory, emissions modelling and life cycle impact characterization modeling was conducted in Emara et al. (2019), with suggestions proposed for PhAC inclusion. Additionally, 27 new CFs for many PhACs have been created (Ortiz et al., 2017) which add to the 60 already available CFs in the USETox™ characterization model used in the EF LCIA method for toxicity, which can also spur the inclusion of PhACs in LCA.

Furthermore, other factors or functions should be taken into consideration for livestock husbandry due to their inherent importance, impact and stark difference between OA and CA - landscape complexity, grassland biodiversity, aesthetics and animal welfare. OA can have clear advantages in these indicators in grassland farming in Germany for example, as more grassland species were found, aesthetics are more appealing according to German standards, and welfare is managed better, although a wide range of indices were found for these categories and are partly independent of the farming system e.g. the use of hedges (Haas et al., 2001). Mattsson et al. (2000) also states that in Sweden, the use of grassland as opposed to only feed concentrate, is viewed positively as it "promotes the domestic environmental goals of biodiversity and aesthetics," but also shows that this category can be subjective to cultural values. Including these somehow in either the functional unit, or LCIA modelling would be essential, and may help reduce the "yield-gap" between OA and CA.

CHAPTER 6

REFERENCES

AGRIBALYSE, 2020. Database v3.0, France: ADEME. [WWW Document]. URL www.ademe.fr/agribalyse-en

Agrios, G., 2005. Plant Patology. Academic Press, London.

Aguilera, E., Guzmán, G., Alonso, A., 2015a. Greenhouse gas emissions from conventional and organic cropping systems in Spain. I. Herbaceous crops. Agron. Sustain. Dev. 35, 713–724. https://doi.org/10.1007/s13593-014-0267-9

Aguilera, E., Guzmán, G., Alonso, A., 2015b. Greenhouse gas emissions from conventional and organic cropping systems in Spain. II. Fruit tree orchards. Agron. Sustain. Dev. https://doi.org/10.1007/s13593-014-0265-y

Almashhadany, D.A., Mohammed, H.I., Muslat, T.A.M., Rashid, R.F., Hassan, R.R., Hassan, A.O., 2022. Antimicrobial Residues in Meat and Meat Products, in: Arshad, D.M.S., Khalid, M.W. (Eds.), Health Risks of Food Additives - Recent Developments and Trends in Food Sector. IntechOpen, Rijeka. https://doi.org/10.5772/intechopen.105784

Andrade, E.P., Bonmati, A., Esteller, L.J., Montemayor, E., Vallejo, A.A., 2021. Performance and environmental accounting of nutrient cycling models to estimate nitrogen emissions in agriculture and their sensitivity in life cycle assessment. Int. J. Life Cycle Assess. https://doi.org/10.1007/s11367-021-01867-4

Andrivon, D., Katsoulas, N., Cirvilleri, G., Conroy, J., Schmutz, U., 2019. Deliverable 3.2: Version 1.1> Available alternatives or Cu and MinOil reduction strategies.

Arikan, O.A., Rice, C., Codling, E., 2008. Occurrence of antibiotics and hormones in a major agricultural watershed. Desalination 226, 121–133. https://doi.org/10.1016/j.desal.2007.01.238

Asbjornsen, H., Hernandez-Santana, V., Liebman, M., Bayala, J., Chen, J., Helmers, M., Ong, C.K., Schulte, L.A., 2014. Targeting perennial vegetation in agricultural landscapes for enhancing ecosystem services. Renew. Agric. Food Syst. 29, 101–125. https://doi.org/10.1017/S1742170512000385

Avadí, A., 2020. Screening LCA of French organic amendments and fertilisers. Int. J. Life Cycle Assess. 25, 698–718. https://doi.org/10.1007/s11367-020-01732-w

Avadí, A., Aissani, L., Pradel, M., Wilfart, A., 2020. Life cycle inventory data on French organic waste treatments yielding organic amendments and fertilisers. Data Br. 28. https://doi.org/10.1016/j.dib.2019.105000

Bartlett, L.J., Newbold, T., Purves, D.W., Tittensor, D.P., Harfoot, M.B.J., 2016. Synergistic impacts of habitat loss and fragmentation on model ecosystems. Proc. R. Soc. B Biol. Sci. 283.

https://doi.org/10.1098/rspb.2016.1027

Bengtsson, J., Ahnström, J., Weibull, A.C., 2005. The effects of organic agriculture on biodiversity and abundance: A meta-analysis. J. Appl. Ecol. 42, 261–269. https://doi.org/10.1111/j.1365-2664.2005.01005.x

Bittman, S., Dedina, M., Howard C.M., Oenema, O., Sutton, M.A., 2014. Options for Ammonia Mitigation: Guidance from the UNECE Task Force on Reactive Nitrogen. Centre for Ecology and Hydrology, Edinburgh, UK.

Blanco-Canqui, H., Francis, C.A., Galusha, T.D., 2017. Does organic farming accumulate carbon in deeper soil profiles in the long term? Geoderma. https://doi.org/10.1016/j.geoderma.2016.10.031

Bockstaller, C., Galland, V., Avadí, A., 2022. Modelling direct field nitrogen emissions using a semi-mechanistic leaching model newly implemented in Indigo-N v3. Ecol. Modell. 472, 110109. https://doi.org/10.1016/j.ecolmodel.2022.110109

Boeckel, B.T.P. Van, Emma, E., Chen, D., Gilbert, M., Robinson, T.P., Grenfell, B.T., Levin, S.A., Bonhoeffer, S., 2017. Reducing antimicrobial use in food animals 357, 1350–1352.

Bos, U., Horn, R., Beck, T., Lindner, J.P., Fischer, M., 2016. LANCA® Characterization Factors for Life Cycle Impact Assessment. Version 2. Stuttgart, DE.

Boulay, A.M., Bare, J., Benini, L., Berger, M., Lathuillière, M.J., Manzardo, A., Margni, M., Motoshita, M., Núñez, M., Pastor, A.V., Ridoutt, B., Oki, T., Worbe, S., Pfister, S., 2016. The WULCA consensus characterization model for water scarcity footprints: Assessing impacts of water consumption based on available water remaining (AWARE).

Brentrup, F., Kusters, J., Lammel, J., Kuhlmann, H., 2000. Methods to estimate on-field nitrogen emissions from crop production as an input to LCA studies in the agricultural sector. Int. J. Life Cycle Assess. 5, 349–357. https://doi.org/10.1007/bf02978670

Bugalho, M.N., Lecomte, X., Gonçalves, M., Caldeira, M.C., Branco, M., 2011. Establishing grazing and grazing-excluded patches increases plant and invertebrate diversity in a Mediterranean oak woodland. For. Ecol. Manage. 261, 2133–2139. https://doi.org/10.1016/j.foreco.2011.03.009

Caballero-López, B., Blanco-Moreno, J.M., Pérez, N., Pujade-Villar, J., Ventura, D., Oliva, F., Sans, F.X., 2010. A functional approach to assessing plant-arthropod interaction in winter wheat. Agric. Ecosyst. Environ. 137, 288–293. https://doi.org/10.1016/j.agee.2010.02.014

Caton, B.P., Fang, H., Manoukis, N.C., Pallipparambil, G.R., 2022. Quantifying insect dispersal distances from trapping detections data to predict delimiting survey radii. J. Appl. Entomol. 146, 203–216. https://doi.org/10.1111/jen.12940

Cespi, D., Beach, E.S., Swarr, T.E., Passarini, F., Vassura, I., Dunn, P.J., Anastas, P.T., 2015. Life cycle inventory improvement in the pharmaceutical sector: assessment of the sustainability combining

PMI and LCA tools. Green Chem. 17, 3390–3400. https://doi.org/10.1039/C5GC00424A

Chaudhary, A., Brooks, T.M., 2018. Land Use Intensity-Specific Global Characterization Factors to Assess Product Biodiversity Footprints. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.7b05570

Chaudhary, A., Verones, F., De Baan, L., Hellweg, S., 2015. Quantifying Land Use Impacts on Biodiversity: Combining Species-Area Models and Vulnerability Indicators. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.5b02507

Clark, M., Tilman, D., 2017. Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. Environ. Res. Lett. 12. https://doi.org/10.1088/1748-9326/aa6cd5

Coutts, S.R., van Klinken, R.D., Yokomizo, H., Buckley, Y.M., 2011. What are the key drivers of spread in invasive plants: Dispersal, demography or landscape: And how can we use this knowledge to aid management? Biol. Invasions 13, 1649–1661. https://doi.org/10.1007/s10530-010-9922-5

Cowling, R.M., Rundel, P.W., Lamont, B.B., Kalin Arroyo, M., Arianoutsou, M., 1996. Plant diversity in mediterranean-climate regions. Trends Ecol. Evol. 11, 362–366. https://doi.org/https://doi.org/10.1016/0169-5347(96)10044-6

Crenna, E., Marques, A., La Notte, A., Sala, S., 2020. Biodiversity Assessment of Value Chains: State of the Art and Emerging Challenges. Environ. Sci. Technol. 54, 9715–9728. https://doi.org/10.1021/acs.est.9b05153

Crooks, K.R., Burdett, C.L., Theobald, D.M., King, S.R.B., Di Marco, M., Rondinini, C., Boitani, L., 2017. Quantification of habitat fragmentation reveals extinction risk in terrestrial mammals. Proc. Natl. Acad. Sci. U. S. A. 114, 7635–7640. https://doi.org/10.1073/pnas.1705769114

Curran, M., De Souza, D.M., Antón, A., Teixeira, R.F.M., Michelsen, O., Vidal-Legaz, B., Sala, S., Milà I Canals, L., 2016. How Well Does LCA Model Land Use Impacts on Biodiversity? - A Comparison with Approaches from Ecology and Conservation. Environ. Sci. Technol. 50, 2782–2795. https://doi.org/10.1021/acs.est.5b04681

Daghrir, R., Drogui, P., 2013. Tetracycline antibiotics in the environment: A review. Environ. Chem. Lett. 11, 209–227. https://doi.org/10.1007/s10311-013-0404-8

Davenport, W., King, M., Schlesinger, M., Biswas, A., 2002. Extractive Metallurgy of Copper, 4th ed. Pergamon.

Davies, K.W., Sheley, R.L., 2007. A Conceptual Framework for Preventing the Spatial Dispersal of Invasive Plants. Weed Sci. 55, 178–184. https://doi.org/10.1614/WS-06-161

De Ponti, T., Rijk, B., Van Ittersum, M.K., 2012. The crop yield gap between organic and conventional agriculture. Agric. Syst. 108, 1–9. https://doi.org/10.1016/j.agsy.2011.12.004

De Soete, W., Debaveye, S., De Meester, S., Van der Vorst, G., Aelterman, W., Heirman, B., Cappuyns, P., Dewulf, J., 2014. Environmental Sustainability Assessments of Pharmaceuticals: An Emerging Need for Simplification in Life Cycle Assessments. Environ. Sci. Technol. 48, 12247–12255. https://doi.org/10.1021/es502562d

Duelli, P., Obrist, M.K., 1998. In search of the best correlates for local organismal biodiversity in cultivated areas. Biodivers. Conserv. 7, 297–309. https://doi.org/10.1023/A:1008873510817

Elshout, P.M.F., Van Zelm, R., Karuppiah, R., Laurenzi, I.J., Huijbregts, M.A.J., 2014. A spatially explicit data-driven approach to assess the effect of agricultural land occupation on species groups. Int. J. Life Cycle Assess. 19, 758–769. https://doi.org/10.1007/s11367-014-0701-x

Emara, Y., Lehmann, A., Siegert, M., Finkbeiner, M., 2019. Modeling Pharmaceutical Emissions and Their Toxicity-Related Effects in Life Cycle Assessment (LCA): A Review. Integr. Environ. Assess. Manag. 15, 6–18. https://doi.org/10.1002/ieam.4100

Essl, F., Lenzner, B., Bacher, S., Bailey, S., Capinha, C., Daehler, C., Dullinger, S., Genovesi, P., Hui, C., Hulme, P.E., Jeschke, J.M., Katsanevakis, S., Kühn, I., Leung, B., Liebhold, A., Liu, C., MacIsaac, H.J., Meyerson, L.A., Nuñez, M.A., Pauchard, A., Pyšek, P., Rabitsch, W., Richardson, D.M., Roy, H.E., Ruiz, G.M., Russell, J.C., Sanders, N.J., Sax, D.F., Scalera, R., Seebens, H., Springborn, M., Turbelin, A., van Kleunen, M., von Holle, B., Winter, M., Zenni, R.D., Mattsson, B.J., Roura-Pascual, N., 2020. Drivers of future alien species impacts: An expert-based assessment. Glob. Chang. Biol. 26, 4880–4893. https://doi.org/10.1111/gcb.15199

ESU, 2012. ESU World Food LCA Databse.

European Commission, 2022. Environmental Footprint Technical Advisory Board [WWW Document]. URL https://ec.europa.eu/transparency/expert-groups-register/screen/expert-groups/consult?do=groupDetail.groupDetail&groupID=3710 (accessed 7.21.22).

European Commission, 2020a. A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system. Communication from the Commission to the European Parliament, the Council, The European Economic and Social Committee and the Committee of the Regions. COM(2020) 381 fin. Brussels.

European Commission, 2020b. A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system. COM(2020) 381 final. Brussels.

European Commission, 2017. PEFCR Guidance document - Guidance for the development of Product Environmental Footprint Category Rules (PEFCRs). version 6.3.

European Commission, 2016. Farms and farmland in the European Union - statistics [WWW Document]. Eurostat. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Farms_and_farmland_in_the_European_Union_-_statistics#Farmland_in_2016

European Commission, 2008a. Commission regulation (EC) no 889/2008 of 5 September 2008 laying down detailed rules for the implementation of council regulation (EC) no 834/2007 on organic production and labelling of organic products with regard to organic production, labelling and co. Off. J. Eur. Union L 250, 1–84.

European Commission, 2008b. 2008/317/EC. Commission decision concerning the non-inclusion of rotenone, extract from equisetum and chinin-hydrochlorid in Annex I to Council Directive 91/414/EEC and the withdrawal of authorisations for plant protection products containing these substa.

European Commission, 2003. Communication from the Commision to the Council and the European Parliament - Integrated Product Policy - Building on Environmental Life-Cycle Thinking COM (2003)302, European Commission of the European COmmunities. Brussels.

European Commission -- Joint Research Centre -- Institute for Environment and Sustainability, 2010. International Reference Life Cycle Data System (ILCD) Handbook -- General guide for Life Cycle Assessment -- Detailed guidance, Constraints. https://doi.org/10.2788/38479

Eurostat, 2022. Area under organic farming [WWW Document]. URL https://ec.europa.eu/eurostat/data/database

Fantke, P., Evans, J., Hodas, N., Apte, J., Jantunen, M., Jolliet, O., McKone, T.E., 2016. Health impacts of fine particulate matter, in: Frischknecht, R., Jolliet, O. (Eds.), Global Guidance for Life Cycle Impact Assessment Indicators: Volume 1. UNEP/SETAC Life Cycle Initiative. Paris, pp. 76–99.

FAO, 2020. Biodiversity and the livestock sector – Guidelines for quantitative assessment – Version 1, LIvestock Environmental Assessment and Performance (LEAP) Partnership. Livestock Environmental Assessment and Performance Partnership (FAO LEAP), Rome. https://doi.org/https://doi.org/10.4060/ca9295en

Fazio, S., Biganzioli, F., De Laurentiis, V., Zampori, L., Sala, S., Diaconu, E., 2018a. Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment methods, version 2, from ILCD to EF 3.0, EUR 29600 EN, European Commission, Ispra, 2018, ISBN 978-92-79-98584-3, doi:10.2760/002447, PUBSY No. JRC114822., EUR 29600 EN, European Commission. Ispra. https://doi.org/10.2760/002447

Fazio, S., Castellani, V., Sala, S., Schau, E.M., Secchi, M., Zampori, L., Diaconu, E., 2018b. Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment method, Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment methods,. https://doi.org/10.2760/671368

Feniuk, C., Balmford, A., Green, R.E., 2019. Land sparing to make space for species dependent on natural habitats and high nature value farmland. Proc. R. Soc. B Biol. Sci. 286, 20191483. https://doi.org/10.1098/rspb.2019.1483

Fischer, J., Abson, D.J., Butsic, V., Chappell, M.J., Ekroos, J., Hanspach, J., Kuemmerle, T., Smith, H.G., Wehrden, H. Von, 2014. Land Sparing Versus Land Sharing : Moving Forward 7, 149–157. https://doi.org/10.1111/conl.12084

Flisch, R., Sinaj, Sokrat, Charles, R., Richner, W., 2009. Grundlagen für die Düngung im Acker- und Futterbau (GRUDAF). Agrarforschung 16, 1–97.

Food and Agriculture Organization, 2022. FAOSTAT [WWW Document]. URL https://www.fao.org/faostat/en/ (accessed 3.10.22).

Food and Agriculture Organization, 2018. Nutrient flows and associated environmental impacts in livestock supply chains. Rome.

Food and Agriculture Organization, 2016. Environmental Performance of Large Ruminant Supply Chains. Rome.

Gabel, V.M., Meier, M.S., Köpke, U., Stolze, M., 2016. The challenges of including impacts on biodiversity in agricultural life cycle assessments. J. Environ. Manage. 181, 249–260. https://doi.org/10.1016/j.jenvman.2016.06.030

Gaudreault, C., Loehle, C., Prisley, S., Solarik, K.A., Verschuyl, J.P., 2020. Are the factors recommended by UNEP-SETAC for evaluating biodiversity in LCA achieving their promises: a case study of corrugated boxes produced in the US. Int. J. Life Cycle Assess. 25, 1013–1026. https://doi.org/10.1007/s11367-020-01765-1

Gerstner, K., Levers, C., Kuemmerle, T., Václavík, T., Pereira, H.M., Seppelt, R., 2017. Assessing land-use effects on European plant diversity using a biome-specific countryside species–area model. Divers. Distrib. 23, 1193–1203. https://doi.org/10.1111/ddi.12608

Gosper, C.R., Stansbury, C.D., Vivian-Smith, G., 2005. Seed dispersal of fleshy-fruited invasive plants by birds: Contributing factors and management options. Divers. Distrib. 11, 549–558. https://doi.org/10.1111/j.1366-9516.2005.00195.x

Grass, I., Loos, J., Baensch, S., Batáry, P., Librán-Embid, F., Ficiciyan, A., Klaus, F., Riechers, M., Rosa, J., Tiede, J., Udy, K., Westphal, C., Wurz, A., Tscharntke, T., 2019. Land-sharing/-sparing connectivity landscapes for ecosystem services and biodiversity conservation. People Nat. 1, 262–272. https://doi.org/10.1002/pan3.21

Grasselly, D., Trédan, M., Colomb, V., 2017. AGRIBALYSE® fruits et légumes. Compléments à la base de données d'inventaires de cycle de vie et démarche d'écoconception de systèmes de culture. ADEME, CTIFL.

Greenpeace, 2019. Feeding the problem: the dangerous intensification of animal farming in Europe. Brussels.

Haas, G., Wetterich, F., Köpke, U., 2001. Comparing intensive , extensified and organic grassland farming in southern Germany by process life cycle assessment. Agric. Ecosyst. Environ. 83, 43–53.

Hansen, S., 2000. Daisy, a flexible soil-plant-atmosphere system model. Report Dept Agric.

Harding, K.G., 2008. A Generic Approach to Environmental Assessment of Microbial Bioprocesses through Life Cycle Assessment (LCA). PhD diss. Univ. Cape T.

Harding, K.G., Harrison, S.T.L., 2016a. Generic flowsheet model for early inventory estimates of industrial microbial processes. II. Downstream processing. South African J. Chem. Eng. 22, 23–33. https://doi.org/10.1016/j.sajce.2016.10.002

Harding, K.G., Harrison, S.T.L., 2016b. Generic flow sheet model for early inventory estimates of industrial microbial processes. I. Flowsheet development, microbial growth and product formation. South African J. Chem. Eng. 22, 34–43. https://doi.org/10.1016/j.sajce.2016.10.003

Hayashi, K., 2020. Inconsistencies between regional- and field-scale biodiversity indicators within life cycle assessment: the case of rice production systems in Japan. Int. J. Life Cycle Assess. 25, 1278–1289. https://doi.org/10.1007/s11367-020-01749-1

Hayashi, K., 2013. Practical recommendations for supporting agricultural decisions through life cycle assessment based on two alternative views of crop production: The example of organic conversion. Int. J. Life Cycle Assess. 18, 331–339. https://doi.org/10.1007/s11367-012-0493-9

Hayashi, K., Nagumo, Y., Domoto, A., 2016. Linking environment-productivity trade-offs and correlated uncertainties: Greenhouse gas emissions and crop productivity in paddy rice production systems. Sci. Total Environ. 571, 134–141. https://doi.org/10.1016/j.scitotenv.2016.07.138

Henle, K., Potts, S., Kunin, Wi., Matsinos, Y., Simila, J., Pantis, J., Grobelnik, V., Penev, L., Settele, J., 2014. Scaling in Ecology and Biodiversity Conservation. Advanced Books. https://doi.org/10.3897/ab.e1169

Higgins, S.I., Richardson, D.M., Cowling, R.M., 1996. Modeling invasive plant spread: The role of plant-environment interactions and model structure. Ecology 77, 2043–2054. https://doi.org/10.2307/2265699

Hobohm, C., Moro-Richter, M., Beierkuhnlein, C., 2021. Distribution and Habitat Affinity of Endemic and Threatened Species: Global and European Assessment BT - Perspectives for Biodiversity and Ecosystems, in: Hobohm, C. (Ed.), . Springer International Publishing, Cham, pp. 233–277. https://doi.org/10.1007/978-3-030-57710-0_11

Hoffman, E., Cavigelli, M.A., Camargo, G., Ryan, M., Ackroyd, V.J., Richard, T.L., Mirsky, S., 2018. Energy use and greenhouse gas emissions in organic and conventional grain crop production: Accounting for nutrient inflows. Agric. Syst. 162, 89–96. https://doi.org/10.1016/j.agsy.2018.01.021

Hole, D.G., Perkins, A., Wilson, J., Alexander, I., Grice, P., Evans, A., 2005. Does organic farming benefit biodiversity ? 122, 113–130. https://doi.org/10.1016/j.biocon.2004.07.018

Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22, 138–147. https://doi.org/10.1007/s11367-016-1246-y

International Union for Conservation of Nature, 2015. IUCN Habitat Classification Scheme, version 3.1. Cambridge, UK.

International Union for Conservation of Nature and Natural Resources: Cambridge UK, 2022. IUCN Red List of Threatened Species [WWW Document]. URL https://www.iucnredlist.org/ (accessed 7.20.22).

IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. https://doi.org/10.5281/ZENODO.6417333

IPCC, 2013. Supplementary material chap. 8 tab 8SM15.

ISO, 2020a. 14040:2006/AMD1:2020 Environmental management — Life cycle assessment — Principles and framework — Amendment 1.

ISO, 2020b. 14044:2006/AMD 2:2020 Environmental management — Life cycle assessment — Requirements and guidelines — Amendment 2.

ISO, 2017. ISO 14044:2006/AMD 1:2017. Environmental management — Life cycle assessment — Requirements and guidelines — Amendment 1.

ISO, 2006a. 14040:2006 Environmental management — Life cycle assessment — Principles and framework [WWW Document].

ISO, 2006b. 14044:2006 Environmental management — Life cycle assessment — Requirements and guidelines. https://doi.org/10.5594/J09750

Jeanneret, P., Baumgartner, D.U., Freiermuth Knuchel, R., Koch, B., Gaillard, G., 2014. An expert system for integrating biodiversity into agricultural life-cycle assessment. Ecol. Indic. 46, 224–231. https://doi.org/10.1016/j.ecolind.2014.06.030

Kapfer, J., Dramstad, W., Pedersen, C., Sickel, H., Heegaard, E., 2022. Diversity patterns in high-latitude grasslands. Appl. Veg. Sci. 25. https://doi.org/10.1111/avsc.12647

Kier, G., Mutke, J., Dinerstein, E., Ricketts, T.H., Küper, W., Kreft, H., Barthlott, W., 2005. Global patterns of plant diversity and floristic knowledge. J. Biogeogr. 32, 1107–1116. https://doi.org/10.1111/j.1365-2699.2005.01272.x

Kier, G., Mutke, J., Dinerstein, E., Ricketts, T.H., Küper, W., Kreft, H., Barthlott, W., Kierl, G., Mutkel, J., Dinerstein, E., Ricketts, T.H., Kreft, H., Barthlott, W., 2020. Global Patterns of Plant Diversity and

Floristic Knowledge Stable URL : https://www.jstor.org/stable/3566381 Linked references are available on JSTOR for this article : Global patterns of plant diversity A and floristic knowledge 32, 1107–1116.

Knapp, S., van der Heijden, M.G.A., 2018. A global meta-analysis of yield stability in organic and conservation agriculture. Nat. Commun. 9, 1–9. https://doi.org/10.1038/s41467-018-05956-1

Knudsen, M.T., Dorca-Preda, T., Djomo, S.N., Peña, N., Padel, S., Smith, L.G., Zollitsch, W., Hörtenhuber, S., Hermansen, J.E., 2019. The importance of including soil carbon changes, ecotoxicity and biodiversity impacts in environmental life cycle assessments of organic and conventional milk in Western Europe. J. Clean. Prod. 215, 433–443. https://doi.org/10.1016/j.jclepro.2018.12.273

Knudsen, M.T., Hermansen, J.E., Cederberg, C., Herzog, F., Vale, J., Jeanneret, P., Sarthou, J.P., Friedel, J.K., Balázs, K., Fjellstad, W., Kainz, M., Wolfrum, S., Dennis, P., 2017. Characterization factors for land use impacts on biodiversity in life cycle assessment based on direct measures of plant species richness in European farmland in the 'Temperate Broadleaf and Mixed Forest' biome. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2016.11.172

Koch, P., Salou, T., 2016. AGRIBALYSE ® : Rapport méthodologique Version 1.3. ADEME.

Koellner, T., Baan, L., Beck, T., Brandão, M., Civit, B., Margni, M., Canals, L.M., Saad, R., Souza, D.M., Müller-Wenk, R., 2013. UNEP-SETAC guideline on global land use impact assessment on biodiversity and ecosystem services in LCA. Int. J. Life Cycle Assess. 18, 1188–1202. https://doi.org/10.1007/s11367-013-0579-z

Koellner, T., Scholz, R.W., 2008. Assessment of land use impacts on the natural environment: Part 2: Generic characterization factors for local species diversity in Central Europe. Int. J. Life Cycle Assess. 13, 32–48. https://doi.org/10.1065/lca2006.12.292.2

Koellner, T., Scholz, R.W., 2007. Impacts on the Natural Environment, Part 1 Land Use in LCA 16 Land Use in LCA (Subject Editor: Llorenç Milà i Canals) Assessment of Land Use Impacts on the Natural Environment Part 1: An Analytical Framework for Pure Land Occupation and Land Use Change Pa. Int J LCA 12, 16–23.

Kok, A., de Olde, E.M., de Boer, I.J.M., Ripoll-Bosch, R., 2020. European biodiversity assessments in livestock science: A review of research characteristics and indicators. Ecol. Indic. 112, 105902. https://doi.org/10.1016/j.ecolind.2019.105902

Korsten, N., Cook, L., 1996. Optimizing Culturing Conditions for Bacillus Subtilis. South African Avocado Grow. Assoc. Yearb. 54–58.

Kristensen, P., 2003. EEA core set of indicators: revised version April 2003. Technical report, EEA.

Kuipers, K.J.J., May, R., Verones, F., 2021. Considering habitat conversion and fragmentation in characterisation factors for land-use impacts on vertebrate species richness. Sci. Total Environ.

801, 149737. https://doi.org/10.1016/j.scitotenv.2021.149737

Kumar, A., Vachan Tirkey, J., Kumar Shukla, S., 2021. Comparative energy and economic analysis of different vegetable oil plants for biodiesel production in India. Renew. Energy 169, 266–282. https://doi.org/10.1016/j.renene.2020.12.128

Lee, S.J., Cho, H., Choi, Y., Choi, W. Il, Chung, H.I., Lim, N.O., Nam, Y., Jeon, S., 2022. Path-finding algorithm as a dispersal assessment method for invasive species with human-vectored long-distance dispersal event. Divers. Distrib. 28, 1214–1226. https://doi.org/10.1111/ddi.13524

Leip, A., Billen, G., Garnier, J., Grizzetti, B., Lassaletta, L., Reis, S., Simpson, D., Sutton, M.A., de Vries, W., Weiss, F., Westhoek, H., 2015. Impacts of European livestock production : nitrogen , sulphur , phosphorus and greenhouse gas emissions , land-use , water eutrophication and biodiversity medium Impacts of European livestock production : nitrogen , sulphur , phosphorus and greenhouse gas. Environ. Res. Lett. 10.

Lindner, J.P., Fehrenbach, H., Winter, L., Bischoff, M., Bloemer, J., Knuepffer, E., 2019. Valuing biodiversity in life cycle impact assessment. Sustain. 11. https://doi.org/10.3390/su11205628

Lindqvist, M., Palme, U., Lindner, J.P., 2016. A comparison of two different biodiversity assessment methods in LCA—a case study of Swedish spruce forest. Int. J. Life Cycle Assess. 21, 190–201. https://doi.org/10.1007/s11367-015-1012-6

Loiseau, E., Aissani, L., Le Féon, S., Laurent, F., Cerceau, J., Sala, S., Roux, P., 2018. Territorial Life Cycle Assessment (LCA): What exactly is it about? A proposal towards using a common terminology and a research agenda. J. Clean. Prod. 176, 474–485. https://doi.org/10.1016/j.jclepro.2017.12.169

Loiseau, E., Roux, P., Junqua, G., Maurel, P., Bellon-Maurel, V., 2014. Implementation of an adapted LCA framework to environmental assessment of a territory: Important learning points from a French Mediterranean case study. J. Clean. Prod. 80, 17–29. https://doi.org/10.1016/j.jclepro.2014.05.059

Lu, C., Yin, J., Zhang, C., Lu, W., 2017. Fed-Batch Fermentation for Spinosad Production in an Improved Reactor. Trans. Tianjin Univ. 23, 530–537. https://doi.org/10.1007/s12209-017-0062-1

Lüscher, G., Ammari, Y., Andriets, A., Angelova, S., Arndorfer, M., Bailey, D., Balázs, K., Bogers, M., Bunce, R.G.H., Choisis, J.P., Dennis, P., Díaz, M., Dyman, T., Eiter, S., Fjellstad, W., Fraser, M., Friedel, J.K., Garchi, S., Geijzendorffer, I.R., Gomiero, T., González-Bornay, G., Guteva, Y., Herzog, F., Jeanneret, P., Jongman, R.H.G., Kainz, M., Kwikiriza, N., López Díaz, M.L., Moreno, G., Nicholas-Davies, P., Nkwiine, C., Opio, J., Paoletti, M.G., Podmaniczky, L., Pointereau, P., Pulido, F., Sarthou, J.P., Schneider, M.K., Sghaier, T., Siebrecht, N., Stoyanova, S., Wolfrum, S., Yashchenko, S., Albrecht, H., Báldi, A., Belényesi, M., Benhadi-Marin, J., Blick, T., Buholzer, S., Centeri, C., Choisis, N., Cuendet, G., De Lange, H.J., Déjean, S., Deltshev, C., Díaz Cosín, D.J., Dramstad, W., Elek, Z., Engan, G., Evtushenko, K., Falusi, E., Finch, O.D., Frank, T., Gavinelli, F., Genoud, D., Gillingham, P.K., Grónás, V., Gutiérrez, M., Häusler, W., Heer, X., Hübner, T., Isaia, M., Jerkovich, G., Jesus, J.B., Kakudidi, E., Kelemen, E., Koncz, N., Kovacs, E., Kovács-Hostyánszki, A., Last, L., Ljubomirov, T., Mandery, K., Mayr, J., Mjelde, A., Muster, C., Nascimbene, J., Neumayer, J., Ødegaard, F., Ortiz Sánchez, F.J., Oschatz, M.L., Papaja-Hülsbergen, S., Paschetta, M., Pavett, M., Pelosi, C., Penksza, K., Pommeresche, R., Popov, V., Radchenko, V., Richner, N., Riedel, S., Scullion, J., Sommaggio, D., Szalkovszki, O., Szerencsits, E., Trigo, D., Vale, J., van Kats, R., Vasilev, A., Whittington, A.E., Wilkes-Allemann, J., Zanetti, T., 2016. Farmland biodiversity and agricultural management on 237 farms in 13 European and two African regions. Ecology 97, 1625. https://doi.org/10.1890/15-1985.1

Lüscher, G., Nemecek, T., Arndorfer, M., Balázs, K., Dennis, P., Fjellstad, W., Friedel, J.K., Gaillard, G., Herzog, F., Sarthou, J.P., Stoyanova, S., Wolfrum, S., Jeanneret, P., 2017. Biodiversity assessment in LCA: a validation at field and farm scale in eight European regions. Int. J. Life Cycle Assess. https://doi.org/10.1007/s11367-017-1278-y

Manyi-Loh, C., Mamphweli, S., Meyer, E., Okoh, A., 2018. Antibiotic Use in Agriculture and Its Consequential Resistance in Environmental Sources: Potential Public Health Implications. Molecules 23. https://doi.org/10.3390/molecules23040795

Martin, A.E., Collins, S.J., Crowe, S., Girard, J., Naujokaitis-Lewis, I., Smith, A.C., Lindsay, K., Mitchell, S., Fahrig, L., 2020. Effects of farmland heterogeneity on biodiversity are similar to—or even larger than—the effects of farming practices. Agric. Ecosyst. Environ. 288, 106698. https://doi.org/https://doi.org/10.1016/j.agee.2019.106698

Mattsson, B., Cederberg, C., Blix, L., 2000. Agricultural land use in life cycle assessment (LCA): Case studies of three vegetable oil crops. J. Clean. Prod. https://doi.org/10.1016/S0959-6526(00)00027-5

Meier, M.S., Hortenhuber, S., Schader, C., Stolze, M., 2017. Organic Farming and Sustainability Life cycle assessments. Fact Sheet. Research Institute of Organic Agriculture, Frick, Vienna.

Meier, M.S., Stoessel, F., Jungbluth, N., Juraske, R., Schader, C., Stolze, M., 2015. Environmental impacts of organic and conventional agricultural products - Are the differences captured by life cycle assessment? J. Environ. Manage. https://doi.org/10.1016/j.jenvman.2014.10.006

Merow, C., Lafleur, N., Silander, J.A., Wilson, A.M., Rubega, M., 2011. Developing dynamic mechanistic species distribution models: Predicting bird-mediated spread of invasive plants across northeastern North America. Am. Nat. 178, 30–43. https://doi.org/10.1086/660295

Ministry of agriculture fisheries and food, 2019. Datos de producción de piensos 2019 - CNCAA.

Montemayor, E., Andrade, E.P., Bonmatí, A., Antón, A., 2022. Critical analysis of life cycle inventory datasets for organic crop production systems. Int. J. Life Cycle Assess. 27, 543–563. https://doi.org/10.1007/s11367-022-02044-x

Montemayor, Erica, Bonmatí, A., Torrellas, M., Camps, F., Ortiz, C., Domingo, F., Riau, V., Antón, A., 2019. Environmental accounting of closed-loop maize production scenarios: Manure as fertilizer and inclusion of catch crops. Resour. Conserv. Recycl. 146, 395–404.

https://doi.org/10.1016/j.resconrec.2019.03.013

Montemayor, E., Bonmatí, A., Torrellas, M., Camps, F., Ortiz, C., Domingo, F., Riau, V., Antón, A., 2019. Environmental accounting of closed-loop maize production scenarios: Manure as fertilizer and inclusion of catch crops. Resour. Conserv. Recycl. 146. https://doi.org/10.1016/j.resconrec.2019.03.013

Mueller, C., De Baan, L., Koellner, T., 2014. Comparing direct land use impacts on biodiversity of conventional and organic milk - Based on a Swedish case study. Int. J. Life Cycle Assess. 19, 52–68. https://doi.org/10.1007/s11367-013-0638-5

Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.H., Smith, P., Klocke, P., Leiber, F., Stolze, M., Niggli, U., 2017. Strategies for feeding the world more sustainably with organic agriculture. Nat. Commun. 8, 1–13. https://doi.org/10.1038/s41467-017-01410-w

Myklestad, Å., Sætersdal, M., 2004. The importance of traditional meadow management techniques for conservation of vascular plant species richness in Norway. Biol. Conserv. 118, 133–139. https://doi.org/10.1016/j.biocon.2003.07.016

Myllyviita, T., Sironen, S., Saikku, L., Holma, A., Leskinen, P., Palme, U., 2019. Assessing biodiversity impacts in life cycle assessment framework - Comparing approaches based on species richness and ecosystem indicators in the case of Finnish boreal forests. J. Clean. Prod. 236, 117641. https://doi.org/10.1016/j.jclepro.2019.117641

Nascimbene, J., Marini, L., Paoletti, M.G., 2012. Organic farming benefits local plant diversity in vineyard farms located in intensive agricultural landscapes. Environ. Manage. 49, 1054–1060. https://doi.org/10.1007/s00267-012-9834-5

Nemecek, T., Bengoa, X., Rossi, V., Humbert, S., Lansche, J., Mouron, P., 2015. World Food LCA Database: Methodological guidelines for the life cycle inventory of agricultural products. Version 3.5.

Nemecek, T., Dubois, D., Huguenin-elie, O., Gaillard, G., 2011. Life cycle assessment of Swiss farming systems : I . Integrated and organic farming. Agric. Syst. 104, 217–232. https://doi.org/10.1016/j.agsy.2010.10.002

Nemecek, T., Kägi, T., 2007. Life cycle inventories of Agricultural Production Systems. Ecoinvent 1–360.

Newbold, T., Hudson, L.N., Hill, S.L.L., Contu, S., Lysenko, I., Senior, R.A., Börger, L., Bennett, D.J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M.J., Feldman, A., Garon, M., Harrison, M.L.K., Alhusseini, T., Ingram, D.J., Itescu, Y., Kattge, J., Kemp, V., Kirkpatrick, L., Kleyer, M., Correia, D.L.P., Martin, C.D., Meiri, S., Novosolov, M., Pan, Y., Phillips, H.R.P., Purves, D.W., Robinson, A., Simpson, J., Tuck, S.L., Weiher, E., White, H.J., Ewers, R.M., MacE, G.M., Scharlemann, J.P.W., Purvis, A., 2015. Global effects of land use on local terrestrial biodiversity. Nature 520, 45–50. https://doi.org/10.1038/nature14324

Newbold, T., Oppenheimer, P., Etard, A., Williams, J.J., 2020. Tropical and Mediterranean biodiversity is disproportionately sensitive to land-use and climate change. Nat. Ecol. Evol. 4, 1630–1638. https://doi.org/10.1038/s41559-020-01303-0

Nitschelm, L., Auberger, J., Chambaut, H., Dauguet, S., Espagnol, S., Gac, A., Le Gall, C., Malnoé, C., Perrin, A., Ponchant, P., Renaud-Gentié, C., Roinsard, A., Sautereau, N., Tailleur, A., van der Werf, H.M.., 2020. Rapport du projet ACV Bio, Analyse du cycle de vie de produits issus de l'agriculture biologique française.

Nitschelm, L., Aubin, J., Corson, M.S., Viaud, V., Walter, C., 2016. Spatial differentiation in Life Cycle Assessment LCA applied to an agricultural territory: Current practices and method development. J. Clean. Prod. 112, 2472–2484. https://doi.org/10.1016/j.jclepro.2015.09.138

O'Niell, J., 2016. TACKLING DRUG-RESISTANT INFECTIONS GLOBALLY : FINAL REPORT AND RECOMMENDATIONS THE REVIEW ON ANTIMICROBIAL RESISTANCE.

Ortiz, S., García, D., García-encina, P.A., Irusta-mata, R., 2017. The potential ecotoxicological impact of pharmaceutical and personal care products on humans and freshwater , based on USEtox ™ characterization factors . A Spanish case study of toxicity impact scores. Sci. Total Environ. 609, 429–445. https://doi.org/10.1016/j.scitotenv.2017.07.148

Pampuro, N., Busato, P., Cavallo, E., 2018. Gaseous emissions after soil application of pellet made from composted pig slurry solid fraction: Effect of application method and pellet diameter. Agric. 8. https://doi.org/10.3390/agriculture8080119

Pieper, M., Michalke, A., Gaugler, T., 2020. Calculation of external climate costs for food highlights inadequate pricing of animal products. Nat. Commun. 11, 1–13. https://doi.org/10.1038/s41467-020-19474-6

Pighinelli, L., 2019. Methods of Chitin Production a Short Review. Am. J. Biomed. Sci. Res. 3, 307–314. https://doi.org/10.34297/ajbsr.2019.03.000682

Pinheiro, J.C., Bates, D.M., 2000. Mixed-Effects Models in S and S-PLUS. Springer.

Pinheiro, J.C., Bates, D.M., DebRoy, S., Sakar, D., Team, R.C., 2022. nlme: Linear and Nonlinear Mixed Effects Models.

Ponce, C., Bravo, C., de León, D.G., Magaña, M., Alonso, J.C., 2011. Effects of organic farming on plant and arthropod communities: A case study in Mediterranean dryland cereal. Agric. Ecosyst. Environ. 141, 193–201. https://doi.org/10.1016/j.agee.2011.02.030

Ponisio, L.C., M'gonigle, L.K., Mace, K.C., Palomino, J., Valpine, P. De, Kremen, C., 2015. Diversification practices reduce organic to conventional yield gap. Proc. R. Soc. B Biol. Sci. 282. https://doi.org/10.1098/rspb.2014.1396

Poore, J., Nemecek, T., 2018. Reducing food's environmental impacts through producers and consumers.

Science (80-.). 360, 987–992. https://doi.org/10.1126/science.aaq0216

Posada-Uribe, L.F., Romero-Tabarez, M., Villegas-Escobar, V., 2015. Effect of medium components and culture conditions in Bacillus subtilis EA-CB0575 spore production. Bioprocess Biosyst. Eng. 38, 1879–1888. https://doi.org/10.1007/s00449-015-1428-1

Posch, M., Seppälä, J., Hettelingh, J., Johansson, M., 2008. The role of atmospheric dispersion models and ecosystem sensitivity in the determination of characterisation factors for acidifying and eutrophying emissions in LCIA 477–486. https://doi.org/10.1007/s11367-008-0025-9

Prasuhn, V., 2006. Erfassung der PO4-Austräge für die Ökobilanzierung - SALCA-Phosphor. Agroescope Reckenholz 20.

Proença, V.M., Pereira, H.M., Guilherme, J., Vicente, L., 2010. Plant and bird diversity in natural forests and in native and exotic plantations in NW Portugal. Acta Oecologica 36, 219–226. https://doi.org/10.1016/j.actao.2010.01.002

Puig-Montserrat, X., Stefanescu, C., Torre, I., Palet, J., Fàbregas, E., Dantart, J., Arrizabalaga, A., Flaquer, C., 2017. Effects of organic and conventional crop management on vineyard biodiversity. Agric. Ecosyst. Environ. 243, 19–26. https://doi.org/10.1016/j.agee.2017.04.005

Rejmánek, M., Richardson, D.M., 2013. Trees and shrubs as invasive alien species - 2013 update of the global database. Divers. Distrib. 19, 1093–1094. https://doi.org/10.1111/ddi.12075

Rey, P.J., Manzaneda, A.J., Valera, F., Alcántara, J.M., Tarifa, R., Isla, J., Molina-Pardo, J.L., Calvo, G., Salido, T., Gutiérrez, J.E., Ruiz, C., 2019. Landscape-moderated biodiversity effects of ground herb cover in olive groves: Implications for regional biodiversity conservation. Agric. Ecosyst. Environ. 277, 61–73. https://doi.org/10.1016/j.agee.2019.03.007

Rijtema, P.E., Kroes, J.G., 1991. Nitrogen Modeling on a Regional Scale, in: Bogárdi, I., Kuzelka, R.D., Ennenga, W.G. (Eds.), Nitrate Contamination. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 81–95.

Ripoll-Bosch, R., de Boer, I.J.M., Bernués, A., Vellinga, T. V., 2013. Accounting for multi-functionality of sheep farming in the carbon footprint of lamb: A comparison of three contrasting Mediterranean systems. Agric. Syst. https://doi.org/10.1016/j.agsy.2012.11.002

Rosenbaum, R.K., Bachmann, T.M., Gold, L.S., Huijbregts, M.A.J., Jolliet, O., Juraske, R., Koehler, A., Larsen, H.F., MacLeod, M., Margni, M., McKone, T.E., Payet, J., Schuhmacher, M., Van De Meent, D., Hauschild, M.Z., 2008. USEtox - The UNEP-SETAC toxicity model: Recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. Int. J. Life Cycle Assess. 13, 532–546. https://doi.org/10.1007/s11367-008-0038-4

Rosenbaum, R.K., Hauschild, M.Z., Boulay, A.-M., Fantke, P., Laurent, A., Núñez, M., Vieira, M., 2018. Life Cycle Impact Assessment, in: Hauschild, M.Z., Rosenbaum, R.K., Olsen, S.I. (Eds.), Life Cycle

Assessment: Theory and Practice. Springer International Publishing, Cham, pp. 167–270. https://doi.org/10.1007/978-3-319-56475-3_10

Rosenzweig, W.L., 1995. Species diversity in space and time. Cambridge University Press, Cambridge, UK.

Rowe, G.E., Margaritis, A., 2004. Bioprocess Design and Economic Analysis for the Commercial Production of Environmentally Friendly Bioinsecticides From Bacillus thuringiensis HD-1 kurstaki. Wiley Intersci. https://doi.org/10.1002/bit.20146

Rundel, P.W., Arroyo, M.T.K., Cowling, R.M., Keeley, J.E., Lamont, B.B., Vargas, P., 2016. Mediterranean Biomes: Evolution of Their Vegetation, Floras, and Climate. Annu. Rev. Ecol. Evol. Syst. 47, 383–407. https://doi.org/10.1146/annurev-ecolsys-121415-032330

Said Al Hoqani, H.A., AL-Shaqsi, N., Hossain, M.A., Al Sibani, M.A., 2020. Isolation and optimization of the method for industrial production of chitin and chitosan from Omani shrimp shell. Carbohydr. Res. 492, 108001. https://doi.org/10.1016/j.carres.2020.108001

Schneider, M.K., Lüscher, G., Jeanneret, P., Arndorfer, M., Ammari, Y., Bailey, D., Balázs, K., Báldi, A., Choisis, J.P., Dennis, P., Eiter, S., Fjellstad, W., Fraser, M.D., Frank, T., Friedel, J.K., Garchi, S., Geijzendorffer, I.R., Gomiero, T., Gonzalez-Bornay, G., Hector, A., Jerkovich, G., Jongman, R.H.G., Kakudidi, E., Kainz, M., Kovács-Hostyánszki, A., Moreno, G., Nkwiine, C., Opio, J., Oschatz, M.L., Paoletti, M.G., Pointereau, P., Pulido, F.J., Sarthou, J.P., Siebrecht, N., Sommaggio, D., Turnbull, L.A., Wolfrum, S., Herzog, F., 2014. Gains to species diversity in organically farmed fields are not propagated at the farm level. Nat. Commun. 5, 1–9. https://doi.org/10.1038/ncomms5151

Schrama, M., de Haan, J.J., Kroonen, M., Verstegen, H., Van der Putten, W.H., 2018. Crop yield gap and stability in organic and conventional farming systems. Agric. Ecosyst. Environ. 256, 123–130. https://doi.org/10.1016/j.agee.2017.12.023

Schryver, A.M. De, Goedkoop, M.J., 2010. Uncertainties in the application of the species area relationship for characterisation factors of land occupation in life cycle assessment 682–691. https://doi.org/10.1007/s11367-010-0205-2

Scialabba, N.E.H., Mller-Lindenlauf, M., 2010. Organic agriculture and climate change. Renew. Agric. Food Syst. 25, 158–169. https://doi.org/10.1017/S1742170510000116

Secretary of State for Trade statistics, 2022. DataComex [WWW Document]. URL https://datacomex.comercio.es/ (accessed 7.10.22).

Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 485, 229–232. https://doi.org/10.1038/nature11069

Smith, L.G., Kirk, G.J.D., Jones, P.J., Williams, A.G., 2019. The greenhouse gas impacts of converting food production in England and Wales to organic methods. Nat. Commun. 10, 1–10. https://doi.org/10.1038/s41467-019-12622-7

Søgaard, H.T., Sommer, S.G., Hutchings, N.J., Huijsmans, J.F.M., Bussink, D.W., Nicholson, F., 2002. Ammonia volatilization from field-applied animal slurry-the ALFAM model. Atmos. Environ. 36, 3309–3319. https://doi.org/10.1016/S1352-2310(02)00300-X

Solomou, A., Sfougaris, A., 2011. Comparing conventional and organic olive groves in central Greece: Plant and bird diversity and abundance. Renew. Agric. Food Syst. 26, 297–316. https://doi.org/10.1017/S1742170511000111

Souza, D.M., Teixeira, R.F.M., Ostermann, O.P., 2015. Assessing biodiversity loss due to land use with Life Cycle Assessment: are we there yet? Glob. Chang. Biol. 21, 32–47. https://doi.org/10.1111/gcb.12709

Springmann, M., Godfray, H.C.J., Rayner, M., Scarborough, P., 2016. Analysis and valuation of the health and climate change cobenefits of dietary change. Proc. Natl. Acad. Sci. U. S. A. 113, 4146–4151. https://doi.org/10.1073/pnas.1523119113

Struijs, J., Beusen, A., van Jaarsveld, H., Huijbregts, M.A.., 2008. Aquatic Eutrophication. Chapter 6, in: ReCiPe 2008 A Life Cycle Impact Assessment Method Which Comprises Harmonised Category Indicators at the Midpoint and the Endpoint Level. Report I: Characterisation Factors. In press.

Subdirectorate General for International Merchandise Trade, 2019. La balanza comercial agroalimentaria en 2019.

Tailleur, A., Cohan, J., Laurent, F., Lellahi, A., 2012. A simple model to assess nitrate leaching from annual crops for life cycle assessment at different spatial scales., in: 8th International Conference on Life Cycle Assessement in the Agri-Food Sector (LCA Food 2012), 1–4 October 2012,. Corson M.S., van der Werf H.M.G. (Eds), Saint-Malo, France, pp. 903–904.

Tanentzap, A.J., Lamb, A., Walker, S., Farmer, A., 2015. Resolving Conflicts between Agriculture and the Natural Environment. PLoS Biol. 13, 1–13. https://doi.org/10.1371/journal.pbio.1002242

Teixeira, R.F.M., De Souza, D.M., Curran, M.P., Antón, A., Michelsen, O., Milá I Canals, L., 2016. Towards consensus on land use impacts on biodiversity in LCA: UNEP/SETAC Life Cycle Initiative preliminary recommendations based on expert contributions. J. Clean. Prod. 112, 4283–4287. https://doi.org/10.1016/j.jclepro.2015.07.118

Tuck, S.L., Winqvist, C., Mota, F., Ahnström, J., Turnbull, L.A., Bengtsson, J., 2014. Land-use intensity and the effects of organic farming on biodiversity: A hierarchical meta-analysis. J. Appl. Ecol. 51, 746–755. https://doi.org/10.1111/1365-2664.12219

Tuomisto, H.L., Hodge, I.D., Riordan, P., Macdonald, D.W., 2012. Does organic farming reduce environmental impacts?--a meta-analysis of European research. J. Environ. Manage. https://doi.org/10.1016/j.jenvman.2012.08.018

Turbelin, A.J., Malamud, B.D., Francis, R.A., 2017. Mapping the global state of invasive alien species:

patterns of invasion and policy responses. Glob. Ecol. Biogeogr. 26, 78–92. https://doi.org/10.1111/geb.12517

Ugulu, I., Ahmad, K., Khan, Z.I., Munir, M., Wajid, K., Bashir, H., 2021. Effects of organic and chemical fertilizers on the growth, heavy metal/metalloid accumulation, and human health risk of wheat (Triticum aestivum L.). Environ. Sci. Pollut. Res. 28, 12533–12545. https://doi.org/10.1007/s11356-020-11271-4

UNEP-SETAC, 2019. Global Guidance on Environmental Life Cycle Impact Assessment Indicators Volume 2.

Valente, J.J., Bennett, R.E., Gómez, C., Bayly, N.J., Rice, R.A., Marra, P.P., Ryder, T.B., Sillett, T.S., 2022. Land-sparing and land-sharing provide complementary benefits for conserving avian biodiversity in coffee-growing landscapes. Biol. Conserv. 270, 109568. https://doi.org/https://doi.org/10.1016/j.biocon.2022.109568

van der Werf, H.M.G., Knudsen, M.T., Cederberg, C., 2020. Towards better representation of organic agriculture in life cycle assessment. Nat. Sustain. 1–7. https://doi.org/10.1038/s41893-020-0489-6

van Oers, L., Koning, A., Guinée, J., Huppes, G., 2002. Abiotic resource depletion in LCA. Road and Hydraulic Engineering Institute, Ministry of Transport and Water.

van Paassen, M., Braconi, N., Kuling, L., Durlinger, B., Gual, P., 2019. Agri-footprint 5.0, Agri-footprint 5.0.

van Zelm, R., Huijbregts, M.A.J., Den Hollander, H.A., van Jaarsveld, H.A., Sauter, F.J., Struijs, J., van Wijnen, H.J., van De Meent, D., 2008. European characterization factors for human health damage of PM10 and ozone in life cycle impact assessment. Atmos. Environ. 42, 441–453. https://doi.org/10.1016/j.atmosenv.2007.09.072

Verones, F., Bare, J., Bulle, C., Frischknecht, R., Hauschild, M., Hellweg, S., Henderson, A., Jolliet, O., Laurent, A., Liao, X., Lindner, J.P., Maia de Souza, D., Michelsen, O., Patouillard, L., Pfister, S., Posthuma, L., Prado, V., Ridoutt, B., Rosenbaum, R.K., Sala, S., Ugaya, C., Vieira, M., Fantke, P., 2017. LCIA framework and cross-cutting issues guidance within the UNEP-SETAC Life Cycle Initiative. J. Clean. Prod. 161, 957–967. https://doi.org/10.1016/j.jclepro.2017.05.206

Vickery, J.A., Feber, R.E., Fuller, R.J., 2009. Arable field margins managed for biodiversity conservation: A review of food resource provision for farmland birds. Agric. Ecosyst. Environ. 133, 1–13. https://doi.org/10.1016/j.agee.2009.05.012

Walpole, S.C., Prieto-merino, D., Edwards, P., Cleland, J., Stevens, G., Roberts, I., 2012. The weight of nations : an estimation of adult human biomass. BMC Public Health 12, 1. https://doi.org/10.1186/1471-2458-12-439

Ward, M.H., Jones, R.R., Brender, J.D., de Kok, T.M., Weyer, P.J., Nolan, B.T., Villanueva, C.M., van Breda, S.G., 2018. Drinking water nitrate and human health: An updated review. Int. J. Environ. Res. Public Health 15, 1–31. https://doi.org/10.3390/ijerph15071557

Weidema, B.P., 1998. Multi-user test of the data quality matrix for product life cycle inventory data. Int. J. Life Cycle Assess. 3, 259–265. https://doi.org/10.1007/BF02979832

Weidema, B.P., Bauer, C., Hischier, R., Mutel, C., Nemecek, T., Reinhard, J., Vadenbo, C.O., Wenet, G., 2013. Data quality guideline for the ecoinvent database version 3. Ecoinvent Report 1 (v3), Swiss Center For Life Cycle Inventories.

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology. Int. J. Life Cycle Assess. 21, 1218–1230. https://doi.org/10.1007/s11367-016-1087-8

Wernet, G., Conradt, S., Isenring, H.P.D., Jiménez-González, C., Hungerbühler, K., 2010. Life cycle assessment of fine chemical production: a case study of pharmaceutical synthesis. Int. J. Life Cycle Assess. 15, 294–303.

Wilbois, K.P., Schmidt, J.E., 2019. Reframing the debate surrounding the yield gap between organic and conventional farming. Agronomy 9, 1–16. https://doi.org/10.3390/agronomy9020082

Wilson, J.B., Peet, R.K., Dengler, J., Pärtel, M., 2012. Plant species richness: The world records. J. Veg. Sci. 23, 796–802. https://doi.org/10.1111/j.1654-1103.2012.01400.x

Winter, L., Lehmann, A., Finogenova, N., Finkbeiner, M., 2017. Including biodiversity in life cycle assessment – State of the art, gaps and research needs. Environ. Impact Assess. Rev. 67, 88–100. https://doi.org/10.1016/j.eiar.2017.08.006

WMO, 1999. Scientific Assessment of Ozone Depletion: 1998. Global Ozone Research and Monitoring Project - Report No. 44. Geneva.

Wu, J., 2006. Landscape ecology, cross-disciplinarity, and sustainability science. Landsc. Ecol. 21, 1–4. https://doi.org/10.1007/s10980-006-7195-2

Xue, C., Duan, Y., Zhao, F., Lu, W., 2013. Stepwise increase of spinosad production in Saccharopolyspora spinosa by metabolic engineering. Biochem. Eng. J. 72, 90–95. https://doi.org/10.1016/j.bej.2013.01.007

Zaccone, C., Di Caterina, R., Rotunno, T., Quinto, M., 2010. Soil - farming system - food - health: Effect of conventional and organic fertilizers on heavy metal (Cd, Cr, Cu, Ni, Pb, Zn) content in semolina samples. Soil Tillage Res. 107, 97–105. https://doi.org/10.1016/j.still.2010.02.004

A. APPENDIX

Table A-1. Plant protection products authorised under Regulation (EEC) No 2092/91 and carried over by Article 16(3)(c) of Regulation (EC) No 834/2007 (European Commission, 2008a)**.**

Name	Description, compositional requirement, conditions for use
Azadirachtin extracted from Azadirachta indica (Neem tree	Insecticide
Beeswax	Pruning agent
Gelatine	Insecticide
Hydrolysed proteins	Attractant, only in authorized applications in combination with other appropriate products of this list
Lecithin	Fungicide
Plant oils (e.g., **mint oil, pine oil, caraway oil)**	Insecticide, acaricide, fungicide and sprout inhibitor
Pyrethrins extracted from Chrysanthemum cinerariaefolium	Insecticide
Quassia extracted from Quassia amara	Insecticide, repellent
Microorganisms (bacteria, viruses and fungi)	
Spinosad	Insecticide Only where measures are taken to minimize the risk to key parasitoids and to minimize the risk of development of resistance
Diammonium phosphate	Attractant, only in traps
Pheromones	Attractant; sexual behaviour disrupter; only in traps and dispensers
Pyrethroids (only deltamethrin or lambdacyhalothrin)	Insecticide; only in traps with specific attractants; only against Bactrocera oleae and Ceratitis capitata Wied
Ferric phosphate (iron (III) orthophosphate)	Molluscicide
Copper in the form of copper hydroxide, copper oxychloride,	Fungicide. up to 6 kg copper per ha per year

(tribasic) copper sulphate, cuprous oxide, copper octanoate	For perennial crops, Member States may, by derogation from the previous paragraph, provide that the 6 kg copper limit can be exceeded in a given year provided that the average quantity actually used over a 5-year period consisting of that year and of the four preceding years does not exceed 6 kg
Ethylene	Degreening bananas, kiwis and kakis; Degreening of citrus fruit only as part of a strategy for the prevention of fruit fly damage in citrus; Flower induction of pineapple; sprouting inhibition in potatoes and onions
Fatty acid potassium salt (soft soap)	Insecticide
Potassium aluminium (aluminium sulphate) (Kalinite)	Prevention of ripening of bananas
Lime sulphur (calcium polysulphide)	Fungicide, insecticide, acaricide
Paraffin oil	Insecticide, acaricide
Mineral oils	Insecticide, fungicide; only in fruit trees, vines, olive trees and tropical crops (e.g., bananas);
Potassium permanganate	Fungicide, bactericide; only in fruit trees, olive trees and vines.
Quartz sand	Repellent
Sulphur	Fungicide, acaricide, repellent
Calcium hydroxide	Fungicide Only in fruit trees, including nurseries, to control Nectria galligena
Potassium bicarbonate	Fungicide

Table A-2. Minimum surface areas indoors and outdoors and other characteristics of housing in the different species and types of production referred to in Article 10(4) for Bovines, equidae, ovine, caprine and porcine (European Commission, 2008a)**.**

	Indoors area (net area available to animals)		Outdoors area (exercise area, excluding pasturage)
Animal type	**Live weight minimum (kg)**	**m^2/head**	**m^2/head**
Breeding and fattening bovine and equidae	Up to 100	1.5	1.1
	Up to 200	2.5	1.9
	Up to 350	4.0	3
	Over 350	5 with a minimum of 1 m^2/100 kg	3.7 with a minimum of 0.75 m^2/ 100 kg
Dairy cows		6	4.5
Bulls for breeding		10	30
Sheep and goats		1.5 sheep/goat	2.5
		0.35 lamb/kid	0.5
Farrowing sows with piglets up to 40 days		7.5 sow	2.5
Fattening pigs	Up to 50	0.8	0.6
	Up to 85	1.1	0.8
	Up to 110	1.3	1
Piglets	Over 40 days and up to 30 kg	0.6	0.4
Brood pigs		2.5 female	1.9
		6 male If pens are used for natural service: 10 m^2/boar	8.0

Table A-3. Minimum surface areas indoors and outdoors and other characteristics of housing in the different species and types of production referred to in Article 10(4) for Poultry (European Commission, 2008a).

	Indoors area (net area available to animals)			Outdoors area (m^2 of area available in rotation/head)
Animal type	**No animals/m^2**	**cm perch/animal**	**nest**	
Laying hens	6	18	7 laying hens per nest or in case of common nest 120 cm^2/bird	4, provided that the limit of 170 kg of N/ha/year is not exceeded
Fattening poultry (in fixed housing)	10 with a maximum of 21 kg liveweight/m^2	20 (for guinea fowl only)		4 broilers and guinea fowl 4.5 ducks 10 turkeys 15 geese In all the species mentioned above the limit of 170 kg of N/ha/year is not exceeded
Fattening poultry in mobile housing	16 (1) in mobile poultry houses with a maximum of 30 kg liveweight/m^2			2.5, provided that the limit of 170 kg of N/ha/year is not exceeded

(1) Only in the case of mobile houses not exceeding 150 m^2 floor space.

B. APPENDIX

For information regarding the calculation of DQR ratings of PPPs, refer to Tables S4 to S20 in the Supplementary Material Excel file from the open access article, Montemayor et al. (2022).

Table B-1. Organic crop production data from ecoinvent (EI, Wernet et al., 2016), AGRIBALYSE® (AG, AGRIBALYSE®, 2020) life cycle inventory datasets and primary data from the Organic+ project (ORG+).

Crop	Location	Yield	Fertilizer	PPPs inputs	Source
Arable					
Maize grain	Switzerland	7777 kg/ha	Liquid and solid cattle and pig manure Green manure (rapeseed)	Trichogramma	EI
Grain Maize	France, Aquitaine	6000 kg/ha	Average P_2O_5 mineral fertilizer Average K_2O mineral fertilizer Organic or farm manure[1] as N, P_2O_5, K_2O Organic manure mix as N, P2O5, K2O (type not specified)	None	AG
Soft wheat grain, after fava beans, Central Region	France	4000 kg/ha/yr	Organic or farm manure[1] as N and P_2O_5 Horn meal	None	AG
Sunflower grain, Gers	France	1900 kg/ha	Organic or farm manure[1] as N, P_2O_5, K_2O Horn meal Compost (average from green waste, biowaste, sludge, manure) Average P_2O_5 mineral fertilizer Average K_2O mineral fertilizer	None	AG
Winter Rapeseed	France	2200 kg/ha	Organic or farm manure[1] as N, P_2O_5, K_2O Compost (average from green waste, biowaste, sludge, manure) Average P_2O_5 mineral fertilizer Average K_2O mineral fertilizer	None	AG
Fruits					
Palm	Global	7281kg/ha	Poultry manure	Kaolin Sulfur	EI
Apple (full production dataset)	France	450500 kg/ha for 17 production years	Potassium chloride Organic or farm manure[1] as N, P_2O_5, K_2O Horn meal Quicklime	• Copper oxide • Sulfur • *Bacillus thuringiensis* (electricity used as proxy for production*)*	AG

				• Rotenone (Pesticide unspecified[2] used as proxy for production) • Lime • Mineral oil (Petrol used as proxy for production) • Mechanical weeding	
Grape (full production dataset)	France (Languedoc-Roussillon)	291000 kg/ha for 30 production years	Average K_2O mineral fertilizer Magnesium oxide Organic or farm manure[1] as N, P_2O_5, K_2O	• Copper • Sulfur • Pyrethrin (pesticide unspecified[2] used as proxy for production)	AG
Peach (full production dataset)	France	224000 kg/ha for 14 production years	Organic manure mix as N, P_2O_5, K_2O (type not specified)	• Copper • Sulfur • Kaolin • Mineral oil (Petrol used as proxy for production) • *Bacillus thuringiensis* (electricity used as proxy for production*)* • Rotenone (Pesticide unspecified[2] used as proxy for production) • Spinosad (Pesticide unspecified[2] used as proxy for production) • Mechanical weeding	AG
Pear (full production dataset)	France	1269000 kg/ha for 40 years	Horn meal	• Copper • *Bacillus thuringiensis* (electricity used as proxy for production*)* • Kaolin • Lime • Spinosad (pesticide unspecified[2] used as proxy for production) • Sulfur • Mechanical weeding	AG
Walnut (traditional, full production)	France	63000 kg/ha for 48 years	Horn meal	• Mechanical weeding • Copper oxide • *Bacillus thuringiensis* (electricity used as proxy for production*)*	AG
Tomato (greenhouse)	France	103700 kg/ha	• Compost (average from green waste, biowaste, sludge, manure) • Industrial biowaste compost	• Copper oxide • *Bacillus thuringiensis* (electricity used as proxy for production*)* • Lime	AG

			• Organic manure mix as N, P_2O_5, K_2O (type not specified) • Potassium chloride as K_2O	• Spinosad (pesticide unspecified[2] used as proxy for production) • Sulfur	
Melon	France	22000 kg/ha	Organic manure mix as N, P_2O_5, K_2O (type not specified)	• Copper oxide • Sulfur	AG
Aubergine	Turkey	34538 kg/ha	Cow manure Green manure	• Trichoderma harzianum rifai • Reynoutria spp. • Neem oil	ORG+
Tomato (greenhouse)	Spain	50000 kg/ha	• Sheep manure • Commercial liquid fertilizer (Calcium (7) and magnesium) • Potassium sulphate	• Neem oil • Potassium soap • Bacillus thuringiensis • Copper oxychloride • Sulphur • Trichogramma • Nesidiocoris	ORG+
Lemons	Sicily	30000 kg/ha	• Commercial pelletized cow manure • Commercial liquid vegetable-based fertilizer	• Mineral oil • Bordeaux mixture	ORG+
Vegetables					
Potato	Switzerland	22908 kg/ha at a moisture content at storage of 78%.	Organic farm cattle and pig manure Green manure (rapeseed)	Copper oxide	EI
Carrot	France	42500 kg/ha/yr	Average K_2O mineral fertilizer Average P_2O_5 mineral fertilizer Potassium chloride	• Copper oxide • Sulfur • Copper sulfate • Biological pest controls (Pesticide unspecified[2] used as proxy for production) • Mechanical weeding	AG
Spring Squash (tunnel)	France	70000 kg/ha	Organic or farm manure[1] as N, P_2O_5, K_2O Compost (average from green waste, biowaste, slude, manure)	Sulfur	AG
Cauliflower	France	13500 kg/ha	Organic or farm manure[1] as N, P_2O_5, K_2O Quicklime	None	AG
Chicory (root production	France	20000 kg/ha	Organic fertilizer (inorganic chemical production used as proxy for production) Quicklime	• *Bacillus thuringiensis* (electricity used as proxy for production) • Copper oxide • Sulfur • Mechanical weeding	AG
Legumes					

Fava beans	Switzerland	3384 kg/ha at a moisture content at storage of 13%.	Organic farm cattle and pig manure Green manure (rapeseed)	None	EI
Peas	Switzerland	3044 kg/ha, moisture content 13%.	Organic farm cattle and pig manure Green manure (rapeseed)	None	EI
	France	2500 kg/ha/yr	Organic farm manure[1] Average P_2O_5 mineral fertilizer Average K_2O mineral fertilizer	None	AG
Soybean	Switzerland	2806 kg/ha moisture content 11%.	Organic farm cattle and pig manure Green manure (rapeseed)	None	EI

[1]The type of manure was not clearly specified in the methodology, though most likely from cattle, as the composition of average organic French manure is mostly from cattle manure (>60%) (Koch and Salou, 2016).

[2]Pesticide unspecified is a background dataset from ecoinvent which is a European average of all available pesticide datasets in ecoinvent, thus indirectly includes synthetic pesticides not approved in OF in Europe.

Table B-2. Nutrient content of typical organic fertilizers in kg per m3 or ton of organic fertilizer from three different sources, in Catalonia from Sío et al. (2013), in the ecoinvent database (Flisch, R., Sinaj, Sokrat, Charles, R., Richner, 2009) and in the AGRIBALYSE database from methodological document (Koch & Salou, 2016). A hyphen (-) indicates that the source does not have any relevant organic fertilizers for that category.

Type of animal	Type of manure	Stage/ production system	kg N/ m^3 or t			kg P_2O_5 /m^3 or t			kg K_2O/m^3 or t		
			Sío et al., (2013)	Flisch et al. (2009)	Koch & Salou (2016)	Sío et al., (2013)	Flisch et al. (2009)	Koch & Salou (2016)	Sío et al., (2013)	Flisch et al. (2009)	Koch & Salou (2016)
Pig	Slurry	Fattening	5.7	6[a]	5.8[b]	3.6	3.8[a]	3.2[b]	4.2	4.4[a]	4.8[b]
		Breeder	2.9	4.7	-	2.1	3.2	-	3.6	3.2	-
		Piglets (6-20 kg)	3.4	-	-	2.6	-	-	1.7	-	-
		Cull sow	3.4	-	-	2.4	-	-	2.5	-	-
		Mixed/ general pig slurry	-	7.8	3.5	-	7	2.1	-	8.3	2.5

Cow	Slurry	Dairy cow	3.3	4.3	-	1.5	1.8	-	3.4	8	-
		Fattening calf	5.2	-	1.5[c]	1.7	-	0.4[c]	3.6	-	2.4[c]
		Diluted cattle slurry (AG)	-	-	1.6	-	-	0.8	-	-	2.4
		Undiluted cattle slurry	-	4.9	3.5	-	1.2	1.2	-	11.6	3.8
		Average cattle slurry	-	-	2.6	-	-	1.0	-	-	3.1
	Manure	Dairy cow	5.5	4.3	-	2	1.8	-	7.9	8	-
		Beef cow	3	4.3[d]	-	2	1.7[d]	-	5	5.2[d]	-
		Fattening calf	6	5.3	-	5	2.3	-	6	5.5	-
		Average cattle manure	-	-	5.5	-	-	2.3	-	-	7.9
Poultry	Hen	Turkey	32.4[e]/24.9[f]	28	18.5	25.8	23	12.9	20	13	13.8
		Broiler chicken	29.6[e]/22.8[f]	-	19.1	21.1	-	13.9	17.7	-	18.4
		Laying hen	16.3[e]/12.5[f]	-	15.0	10.4	-	21.9	8.0	-	18.2
		Breeding hen	22.6[e]/17.4[f]	-	-	33.9	-	-	23.6	-	-
		Replacement hen	25.4[e]/19.5[f]	-	-	45.8	-	-	25.5	-	-
		Chicken manure	-	34.0	-	-	20.0	-	-	28.0	-

		Hen droppings (manure belt)	-	21.0	-	-	17.0	-	-	11.0	-
		Hen dung manure pit	-	27.0	-	-	30.0	-	-	20.0	-
Sheep and Goats	Manure	Meat Sheep	9.4	-	-	5.0	-	-	10.0	-	-
		Dairy sheep	8.1	-	-	3.2	-	-	8.6	-	-
		sheep manure	-	-	6.7	-	-	4.0	-	-	12.0
		Goat	9.4	8.0[g]	6.1	5.0	3.3[g]	5.2	9.0	16.0[g]	7.0
	Slurry	Dairy sheep	7.3	-	-	3.4	-	-	7.1	-	-
Horses	Manure	Horse (fresh)	5.7	4.4	4.8	2.1	2.5	3.0	8.2	9.8	8.5
Rabbit	Slurry		-	-	7.6	-	-	11.8	-	-	5.9
	Manure	Rabbit	8.4	-	-	10.3	-	-	9.5	-	-
Others		Manure compost	12	- [i]	- [h]	15.6	- [i]	- [h]	12.5	- [i]	- [h]
		Sewage sludge compost	18.8		7.0	23.3		7.0	6.2		1.5
		Sludge from treatment plant [k]	10.5		-	13		-	1.2		-
		Slurry digestate	3.5		-	1.4		-	1.3		-
		Pig manure solid fraction	5.3		-	13.6		-	2.3		-

[a] Mast fed pigs

[b] Refers to pig slurry from outdoor runs

[c] Beef calf slurry, assumed similar to fattening calf

[d] Flisch et al. (2009) states it’s for fattening, full manure, it is assumed to be similar to "beef" category

[e] Sample taken from the hen building or cage except in the case of layers which have been taken from the conveyor belt

[f] Sample taken from manure pit

[g] Represents values for both sheep and goat

[h] See table X of organic fertilizers not included in our values

[i] Flisch et al. (2009) states that the values should only be used for fertilizer design instead of guide values as the nutrient levels fluctuate considerably with different starting materials

[j] There is high variability for these types of organic fertilizers due to the different primary materials used in each industrial plant.

[k] Only agricultural treatment sludge that has been previously treated can be used for agricultural purposes.

Table B-3. Fertilizers and soil conditioners authorized under European organic agriculture regulations (European Commission, 2008) and their possible LCI dataset from available LCA databases.

Fertilizers and soil conditioners	Description	Possible LCI dataset
Farmyard manure	Product comprising a mixture of animal excrements and vegetable matter (animal bedding). Factory farming origin forbidden	Agribalyse: Manure from poultry or cattle, stocked in concrete surface or pit.
Dried farmyard manure and dehydrated poultry manure	Factory farming origin forbidden	Ecoinvent: poultry manure, dried
Composted animal excrements, including poultry manure and	Factory farming origin forbidden	Agribalyse: Compost of cattle manure or swine slurry and straw

composted farmyard manure included		
Liquid animal excrements	Use after controlled fermentation and/or appropriate dilution Factory farming origin forbidden	Agribalyse: digestate, from anaerobic digestion of manure and slurry mix
Composted or fermented household waste	Product obtained from source separated household waste, which has been submitted to composting or to anaerobic fermentation for biogas production Only vegetable and animal household waste Only when produced in a closed and monitored collection system, accepted by the Member State Maximum concentrations in mg/kg of dry matter: cadmium: 0,7; copper: 70; nickel: 25; lead: 45; zinc: 200; mercury: 0,4; chromium (total): 70; chromium (VI	Agribalyse: Compost of green waste
Peat	Use limited to horticulture (market gardening, floriculture, arboriculture, nursery)	Ecoinvent: peat moss production
Mushroom culture wastes	The initial composition of the substrate shall be limited to products of this Annex	Not available
Dejecta of worms (vermicompost) and insects		Not available
Guano		Not available
Composted or fermented mixture of vegetable matter	Product obtained from mixtures of vegetable matter, which have been submitted to composting or to anaerobic fermentation for biogas production	Not available
Products or by-products of animal origin as below: blood meal hoof meal horn meal bone meal or degelatinized bone meal fish meal meat meal feather, hair and 'chiquette' meal wool fur hair dairy products	Maximum concentration in mg/kg of dry matter of chromium (VI): 0	Ecoinvent and Agribalyse: horn meal, blood meal

Products and by-products of plant origin for fertilisers	Examples: oilseed cake meal, cocoa husks, malt culms	Ecoinvent: sugarcane filter cake, coconut cake, soybean meal, flax husks ILCD: sunflower meal, soybean hulls, rapeseed meal Agribalyse: palm kernel meal, coconut fibre ESU: wheat meal, pea meal
Seaweeds and seaweed products	As far as directly obtained by: (i) physical processes including dehydration, freezing and grinding (ii) extraction with water or aqueous acid and/or alkaline solution (iii) fermentation	ecoinvent and Agribalyse: multiple types of seaweed
Sawdust and wood chips	Wood not chemically treated after felling	Ecoinvent: saw dust & wood chips (but for furnace production
Composted bark	Wood not chemically treated after felling	Ecoinvent: debarking softwood process, but this assumes that the bark is not a by-product
Wood ash	From wood not chemically treated after felling	Ecoinvent: treatment of wood ash
Soft ground rock phosphate	Product as specified in point 7 of Annex IA.2. to Regulation (EC) No 2003/2003 of the European Parliament and of the Council (1) relating to fertilisers, 7 Cadmium content less than or equal to 90 mg/kg of P20	Ecoinvent: rock phosphate
Aluminium-calcium phosphate	Product as specified in point 6 of Annex IA.2. of Regulation 2003/2003, Cadmium content less than or equal to 90 mg/kg of P205 Use limited to basic soils (pH > 7,5)	None available (sodium phosphate is available in Ecoinvent)
Basic slag	Products as specified in point 1 of Annex IA.2. of Regulation 2003/2003	Ecoinvent: many types available (from blast furnace)
Crude potassium salt or kainite	Products as specified in point 1 of Annex IA.3. of Regulation 2003/2003	Ecoinvent: many types available
Potassium sulphate, possibly containing magnesium salt	Product obtained from crude potassium salt by a physical extraction process, containing possibly also magnesium salts	Ecoinvent: potassium sulphate

Stillage and stillage extract	Ammonium stillage excluded	Ecoinvent: ethanol production from different cereals, however, an economic allocation would need to be done to account for the impacts of the stillage itself, derived from this dataset.
Calcium carbonate (chalk, marl, ground limestone, Breton ameliorant, (marl), phosphate chalk)	Only of natural origin	Ecoinvent: calcium carbonate
Magnesium and calcium carbonate	Only of natural origin e.g., magnesian chalk, ground magnesium, limestone	Ecoinvent: magnesium carbonate or magnesium production
Magnesium sulphate (kieserite)	Only of natural origin	None available of "natural origin"
Calcium chloride solution	Foliar treatment of apple trees, after identification of deficit of calcium	ILCD and Ecoinvent: calcium chloride
Calcium sulphate (gypsum)	Products as specified in point 1 of Annex ID. of Regulation 2003/2003 Only of natural origin	ILCD: Gypsum
Industrial lime from sugar production	By-product of sugar production from sugar beet	Ecoinvent: beet sugar production. however, an economic allocation would need to be done to account for the impacts of the stillage itself, derived from this dataset.
Industrial lime from vacuum salt production	By-product of the vacuum salt production from brine found in mountains	None
Elemental sulphur	Products as specified in Annex ID.3 of Regulation 2003/ 2003	Ecoinvent: sulphur
Trace elements	Inorganic micronutrients listed in part E of Annex I to Regulation 2003/2003	None available
Sodium chloride	Only mined salt	Ecoinvent
Stone meal and clays		Ecoinvent: stone meal

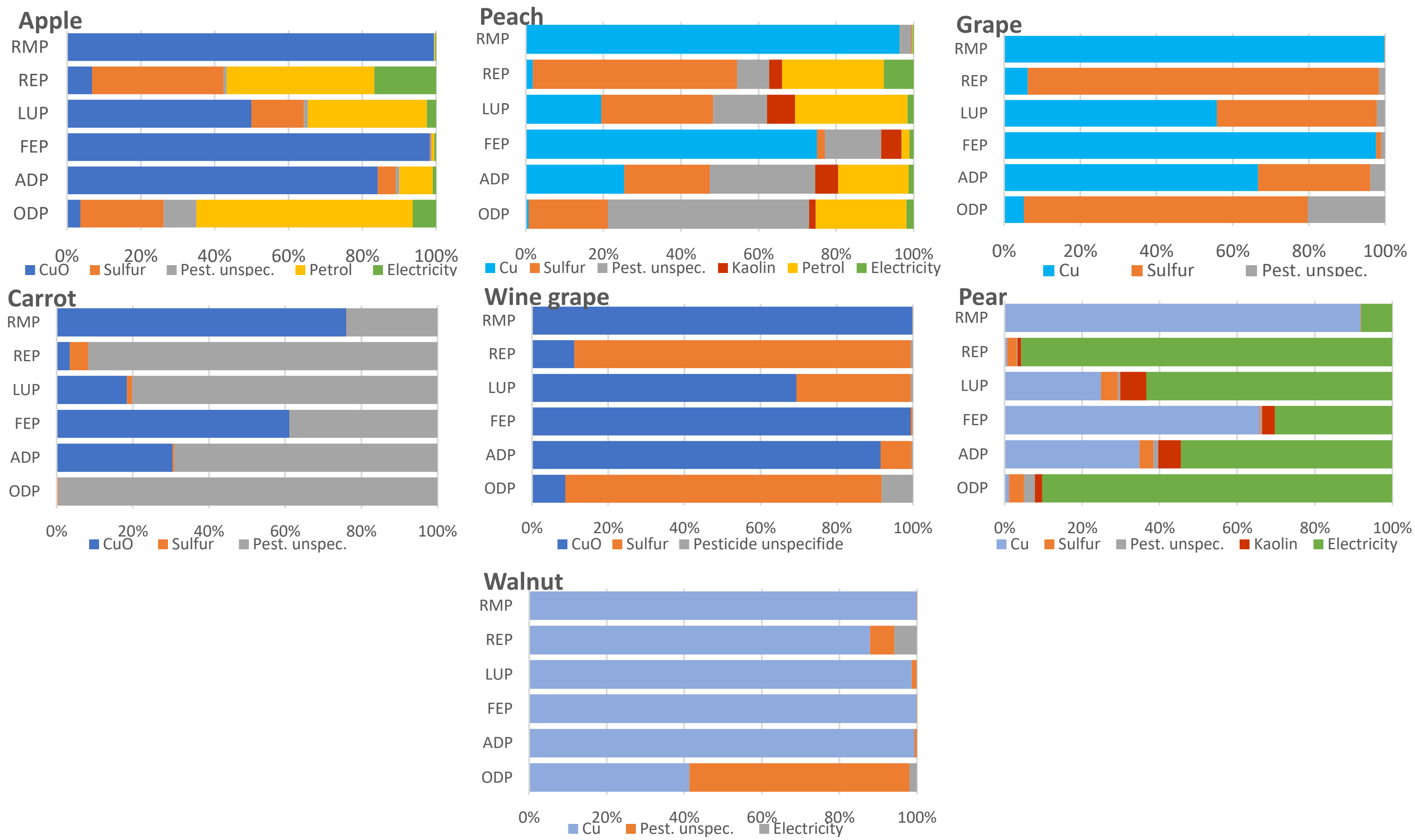


Figure B-1. Contribution of plant protection product manufacturing datasets (copper (II) oxide (CuO), copper ore (Cu), sulfur, kaolin, pesticide unspecified as Spinetoram proxy, electricity as *Bacillus thuringensis* proxy, petrol as mineral oil proxy) to overall PPP manufacturing impact for organic apple, peach and grape, wine grape, pear, walnut and carrots in the AGRIBALYSE database for potential resource mineral use (RMP) and resource energy use (REP), land use (LUP), freshwater eutrophication (FEP), air acidification (ADP), and ozone depletion (ODP). Each crop dataset only has the PPPs listed in the legend of each corresponding graph.

Table B-4. Contribution of fertilizer production within cereal and legume Agribalyse datasets to the total impact for categories climate change (CCP), ozone depletion (ODP), acidification (ADP), freshwater (FEP) and marine (MEP) and terrestrial (TEP) eutrophication, freshwater ecotoxicity (FEx), land use (LUP), resource energy carrier use (REP), and resource mineral use (RMP).

	Soft Wheat	Sunflower				Winter Rapeseed		Pea		Grain maize	
Impact Category	Horn meal	Avg Compost	Horn meal	Avg Min. Fert. P_2O_5	Avg Min. Fert. K_2O	Avg Min. Fert. P_2O_5	Avg Min. Fert. K_2O	Avg Min. Fert. P_2O_5	Avg Min. Fert. K_2O	Avg Min. Fert. P_2O_5	Avg Min. Fert. K_2O
CCP	11.64	9.88	2.54	2.26	0.65	1.12	0.58	2.89	2.62	7.15	0.84
ODP	15.94	6.08	3.65	2.80	0.61	5.85	2.32	2.58	1.79	9.32	0.77
ADP	4.93	5.74	0.31	1.60	0.27	1.04	0.32	5.12	2.73	4.29	0.27
FEP	0.76	0.52	0.09	1.79	0.22	4.97	1.13	3.18	1.26	6.42	0.35
MEP	0.17	0.83	0.06	0.07	0.02	0.08	0.05	0.05	0.05	0.36	0.03
TEP	3.66	11.84	0.22	0.29	0.09	0.21	0.12	1.08	1.05	1.03	0.09
FEx	33.53	5.07	0.76	2.09	105.10	0.91	82.53	0.44	69.39	0.49	0.02
LUP	0.14	0.11	0.04	0.13	0.02	0.20	0.05	0.12	0.05	0.28	0.01
REP	23.61	9.80	5.27	4.84	0.98	10.68	3.89	4.26	2.72	8.50	0.84
RMP	11.26	8.98	3.42	5.05	4.98	6.04	10.77	3.09	9.64	48.03	3.52

Table B-5. Contribution of fertilizer production within vegetable Agribalyse datasets to the total impact for categories climate change (CCP), ozone depletion (ODP), acidification (ADP), freshwater (FEP) and marine (MEP) and terrestrial (TEP) eutrophication, freshwater ecotoxicity (FEx), land use (LUP), resource energy carrier use (REP), and resource mineral use (RMP).

	Cauliflower	Carrot				Squash	Chicory root	
Impact Category	Quicklime	KCl, as K_2O	Wheat straw	Avg Min. Fert. P_2O_5	Avg Min. Fert. K_2O	Average compost	Inorganic chemical	Quicklime
CCP	20.63	2.78	28.58	4.13	4.37	25.16	4.95	2.61
ODP	16.85	1.19	23.57	2.41	1.95	19.16	3.84	1.02
ADP	1.21	1.59	28.21	5.43	3.37	24.56	4.92	0.38
FEP	1.99	3.99	9.97	14.78	6.82	7.60	5.05	0.07
MEP	0.34	0.72	31.87	0.96	1.24	16.27	0.26	0.03
TEP	0.62	0.83	32.02	1.22	1.39	45.63	2.22	0.22
FEx	15.10	33.95	1.43	0.27	49.27	1.50	1.50	0.19
LUP	0.11	0.46	0.80	1.43	0.71	-1.59	0.07	0.00
REP	13.93	2.30	26.99	5.20	3.86	11.84	4.31	0.87
RMP	0.49	5.77	23.52	2.68	9.76	1.35	6.32	0.02

Table B-6. Contribution of fertilizer production within fruit and nut Agribalyse datasets to the total impact for categories climate change (CCP), ozone depletion (ODP), acidification (ADP), freshwater (FEP) and marine (MEP) and terrestrial (TEP) eutrophication, freshwater ecotoxicity (FEx), land use (LUP), resource energy carrier use (REP), and resource mineral use (RMP).

	Tomato				Apple				Pear		Grape		Walnut
Impact Category	KCl, as K2O	Avg Compost	Lime	Biowaste compost	Quicklime	KCl, as K2O	Horn meal	Lime	Horn meal	Lime	MgO	Avg Min. Fert. K_2O	Horn meal
CCP	0.21	16.69	0.02	1.33	0.1563	0.44	0.98	0.026	3.10	0.000	1.11	1.52	4.80
ODP	0.20	10.84	0.02	0.76	0.0456	0.22	0.80	0.015	2.74	0.000	0.06	1.05	6.47
ADP	0.14	20.38	0.02	6.10	0.0134	0.18	0.17	0.010	0.56	0.000	0.24	1.36	0.84
FEP	0.45	5.86	0.04	0.48	0.0042	0.50	0.13	0.053	0.59	0.001	0.19	1.26	0.81
MEP	0.11	20.51	0.03	1.20	0.0023	0.03	0.04	0.001	0.18	0.000	0.01	0.05	0.50
TEP	0.06	40.03	0.02	5.34	0.0074	0.09	0.14	0.004	0.44	0.000	0.14	0.49	0.67
FEx	17.39	3.99	0.12	6.08	0.0015	2.16	0.01	0.001	0.03	0.000	0.03	2.49	1.84
LUP	-0.06	-1.81	-0.04	-0.20	0.0271	2.07	2.49	0.059	10.35	0.001	0.38	11.23	27.38
REP	0.16	8.71	0.02	0.42	0.0337	0.30	1.00	0.022	2.60	0.000	0.20	1.83	8.27
RMP	0.12	1.16	0.00	0.05	0.0007	0.49	0.21	0.076	0.69	0.001	0.01	2.22	1.88

Table B-7. Ratio of N-NH3 emitted per total ammoniacal nitrogen (TAN) content as a function of fertilizer type, machinery employed for application, time between fertilizer deposition and incorporation and atmospheric conditions (adapted from Bittman, et al., 2014; Søgaard et al., 2002)

Atmospheric conditions	Unfavourable atmospheric conditions (windspeed > 2m·s^{-1}, air temperature > 18°C)	Average atmospheric conditions between unfavourable and favourable	Favourable atmospheric conditions (low mean air temperature 9°C, low wind speed <1.6m/s)
Liquid pig or cow slurry or digestate	**NH_3/TAN**	**NH_3/TAN**	**NH_3/TAN**
Broad sprayer, not incorporated	0.827	0.611	0.4800
Broad sprayer, incorporated in 24h	0.5789	0.4277	0.3360
Hose, not incorporated	0.477	0.353	0.2770
Hose, incorporated in 24h	0.3339	0.2471	0.1939
Injection	0	0	0
Soil manure (Poultry or cow)	**NH_3/TAN**	**NH_3/TAN**	**NH_3/TAN**
Surface deposition, not incorporated	0.2481	0.1833	0.1440
Surface deposition, incorporated in 24h	0.17367	0.12831	0.1008

Table B-8. Life cycle inventory for 1 kg of Spinosad using the CeBER Bioprocess Modeller (Centre for Bioprocess Engineering Research (Harding and Harrison, 2016a, 2016b). The specific species needed for Spinosad, Saccharopolyspora spinosa, was not available, thus, erythromycin was used as a proxy as the bacteria that produce both substances were from the same genus, Saccharopolyspora. However, model parameters were adapted to Spinosad production using data from (Lu et al., 2017).

INPUTS	Quantity	Units	OUTPUTS	Quantity	Units
Saccharopolyspora spinosa inoculum	0.001606	kg	**Water emissions:**		
Distilled water	0.001943	m3	Water	0.00108	
Antifoaming agent (propylene glycol)	0.01386	kg	Antifoam	0.0076	
Glucose (Carbon source)	0.0555	kg	Saccharopolyspora spinosa	0.02807	
Maltose (Carbon source)	0.0555	kg	Glucose	0.303	g

Oxygen (aeration)	1.48	kg	Maltose	0.303	g
Nitrogen (aeration)	5.567	kg	Yeast extract	0.966	g
Yeast extract (Nitrogen source)	0.0368	kg	Corn Stover	0.966	g
Corn stover (Nitrogen source)	0.0368	kg	Acetone	0.059	kg
Acetone (purification)	0.0961	kg	Spinosad	0.015	kg
Filter paper (filtration)	0.0426	kg	PO_4^-	0.731	g
Electricity	10.49	MJ	SO_4^-	0.154	
Steam	0.000211	ton	**Air emissions:**		
Chilled water	0.0313	m3	O_2	1.332	kg
			N_2	5.567	kg
			CO_2	0.198	kg
			Solid waste:		
			Filter paper	0.043	kg
			Chemical Oxygen Demand (COD	0.125	kg

Table B-9. Life cycle inventory for 1 kg of Bacillus subtilis using the CeBER Bioprocess Modeller (Centre for Bioprocess Engineering Research (Harding and Harrison, 2016a, 2016b). Model parameters from (Pighinelli, 2019; Posada-Uribe et al., 2015) were used to guide types of processes to use in the model.

INPUTS	Quantity	Units	OUTPUTS	Quantity	Units
***Bacillis subtilis* inoculum**	0.00447	kg	**Water emissions:**		
Distilled water	0.00817	m^3	Water	0.0074	m^3
Antifoaming agent (propylene glycol)	0.0376	kg	Antifoam	0.036	kg
Glucose (Carbon source)	0.2703	kg	*Bacillis subtilis*	0.0030	kg
Oxygen (aeration from air)	1.814	kg	Glucose	1.547	g
Nitrogen (aeration from air)	6.6825	kg	Peptone	1.635	g
Yeast extract (Nitrogen source)	0.0358	kg	Yeast extract	1.635	g
Peptone (Nitrogen source)	0.0358	kg	PO_4^-	1.237	g
Electricity	1.406	MJ	**Air emissions:**		
Steam	0.000609	ton	O_2	1.53	kg
Chilled water	0.0881	m^3	N_2	6.82	kg
			CO_2	0.389	kg
			Solid waste:		
			None		
			Chemical Oxygen Demand (COD	0.0134	kg

Table B-10. Life cycle inventory for 1 kg of Chitosan using data from (Pighinelli, 2019; Said Al Hoqani et al., 2020).

INPUTS	Quantity (kWh/kg)	Units
Processing of seafood waste		
Electricity - Fume hood ventilation of washed seafood waste	1032.47	kWh/kg
Electricity - Grinding into pieces (for 10 mins)	0.0025	kWh/kg
Electricity - Drying in hot air oven	25.02	kWh/kg
Demineralization		
Electricity - Agitation at 250 rpm, 2h	0.015	kWh/kg
Hydrochloric acid (1M)	0.22	L
Deproteination		
NaOH	10	L
Electricity – Agitation, 3h	0.0225	kWh/kg
Electricity – dried in oven, 50℃, 12h	50.04	kWh/kg
Discoloration		
H_2O_2 (30)	10	L
Chitosan production		
NaOH		
Electricity – reaction in autoclave, 121℃, 15 mins	4800	kWh/kg
Electricity – Dried in oven, 50℃, 12h	50.04	kWh/kg

C. APPENDIX

Table C-1. Additional details of case study farms used to test the performance of biodiversity loss models.

Farm details	ES1	ES2	NO1
Number of ewes, age 60 -365 days (heads·year^{-1})	4	31	0
Number of ewes, age 365 - 517 days (heads·year^{-1})	1	12	21
Number of rams (heads·year^{-1})	3	7	2
Ram yield (ton·farm^{-1}·year^{-1})	0.00975	0.13	-

Pasture use for autumn, spring, summer (days)		275			335			184	
Stable use for winter and fed feed (days)		90			30			181	
Age of ewe at slaughter (days)		>517			>517			1095	
Age of lamb at slaughter (days)		75			60			167	
Feed consumption (days fed feed/year) (%)		25%			0.16			0.495	
Land use type	Area ($ha \cdot farm^{-1} \cdot year^{-1}$)	Ecoregion	Land use type, intensity	Area ($ha \cdot farm^{-1} \cdot year^{-1}$)	Ecoregion	Land use type, intensity	Area ($ha \cdot farm^{-1} \cdot year^{-1}$)	Ecoregion	Land use type, intensity
Pasture	50	Pyrenees conifer and mixed forests[1]	Pasture, minimal	195	Pyrenees conifer and mixed forests[1]	Pasture, minimal	7.2	Sarmatic mixed forests[1]	Pasture, minimal
Stable for animals	0.021	Pyrenees conifer and mixed forests[1]	Urban, minimal	0.03	Pyrenees conifer and mixed forests[1]	Urban, minimal	0.03	Sarmatic mixed forests[1]	Urban, minimal

Stable for farming equipment	0.042	Pyrenees conifer and mixed forests[1]	Urban, intense	-	-	-	-	-	-
Feed grown on-site	0	-	-	6	Pyrenees conifer and mixed forests[1]	Cropland, light	5.4	Sarmatic mixed forests[1]	Cropland, minimal
Purchased complementary feed for ewes, rams and gimmers							Purchased feed for all animals		
Maize	2.21E-02	East European forest steppe[1]	Cropland, intense	1.01E-01	East European Forest steppe[1]	Cropland, intense	-	-	-
	2.04E-02	Cerrado	Cropland, intense	9.34E-02	Cerrado	Cropland, intense	-	-	-
	4.35E-03	Northeastern Spain & Southern France Mediterranean forests	Cropland, intense	1.99E-02	Northeastern Spain & Southern France Mediterranean forests	Cropland, intense	-	-	-
Barley	1.04E-01	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	2.97E-02	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	1.93E-03	Sarmatic mixed forests[1]	Cropland, light
Purchased compound feed for lamb									
Oat	-	-		-	-		1.68E-02	Sarmatic mixed forests[1]	Cropland, light
Maize	8.63E-04	East European Forest steppe[1]	Cropland, intense	5.04E-03	East European Forest steppe[1]	Cropland, intense	-	-	
	7.98E-04	Cerrado	Cropland, intense	4.67E-03	Cerrado	Cropland, intense	-	-	

	1.70E-04	Northeastern Spain & Southern France Mediterranean forests	Cropland, intense	9.94E-04	Northeastern Spain & Southern France Mediterranean forests	Cropland, intense	-	-	
Wheat	6.01E-03	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	3.52E-02	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	1.92E-02	Sarmatic mixed forests[1]	Cropland, light
Barley	5.86E-03	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	3.42E-02	Iberian sclerophyllous and semi-deciduous forests	Cropland, intense	-	-	
Soy	3.16E-03	Cerrado	Cropland, intense	1.85E-02	Cerrado	Cropland, intense	2.72E-02	Cerrado	Cropland, intense
	2.05E-04	Central forest/grasslands transition zone	Cropland, intense	1.44E-02	Central forest/grasslands transition zone	Cropland, intense	7.56E-03	Southern Great Lakes forests[1]	Cropland, intense
Palm oil	1.97E-06	Sumatran peat swamp forests	Cropland, intense	1.15E-05	Sumatran peat swamp forests	Cropland, intense	-	-	
Rye	-	-	-	-	-	-	8.23E-03	Sarmatic mixed forests[1]	Cropland, light
Peas	-	-	-	-	-	-	2.09E-03	Sarmatic mixed forests[1]	Cropland, light
Green beans	-	-	-	-	-	-	1.03E-03	Sarmatic mixed forests[1]	Cropland, light

Sugarcane	-	-	-	-	-	-	Maputaland coastal forest mosaic	Cropland, intense
	-	-	-	-	-	-	Upper Gangetic Plains moist deciduous forests	Cropland, intense
	-	-	-	-	-	-	Central American dry forests	Cropland, intense
	-	-	-	-	-	-	Northwestern thorn scrub forests	Cropland, intense
	-	-	-	-	-	-	Sahelian Acacia savanna	Cropland, intense

[1] This ecoregion is within the biome Temperate broadleaf and mixed forest biome.

Table C-2. Types of feed consumed in case studies ES1 and ES2 (Spain), their origin of cultivation, percent imported from that location and yield (FAOSTAT (Food and Agriculture Organization, n.d.))

Crop	Origin	Percent imported from that location	Comments	Yield (kg/ha)
Maize	Ukraine	40%		6410
	Brazil	31%		5340
	France	11%	Others: 18%	8670
Wheat	Spain	98%		3190
Barley	Spain	95%		3360
Soy flour	Brazil	51%		3190
	USA	42%	Others:7%	3330
Wheat bran	Spain	98%		17160
Palm oil	Indonesia	99%		6410

Table C-3. Types of feed consumed in case study NO1, Norway (Compound feed Brand Natura Drov), the percent content, and yield (Food and Agriculture Organization, n.d.))

Ingredients	Origen	Percent content in 1 kg of compound feed	Yield, kg/ha
wheat (local)	Norway	22.0%	4595
soy (imported)	Brazil	21.7%	3194
	Canada	5.4%	2870
oat (local)	Norway	17.0%	4053
sugarcane	Mozambique	1.4%	64641
	India	0.7%	74752
	Guatemala	0.6%	113705
	Pakistan	0.7%	62718
	Sudan	0.5%	80284
Barley	Norway	2.0%	4135
Rye	Norway	10.0%	4863
Peas	Norway	3.0%	7800
Green beans	Norway	2.0%	5739

Table C-4. Characterization factors for relevant ecoregions in units PSL/m^2 from Chaudhary and Brooks (2018).

Land use	Management type	Mammals	Birds	Amphibians	Reptiles	Plants	Aggregated
Ecoregion PA0436							
Pasture	minimal	5.63E-13	**1.11E-12**	1.27E-13	6.32E-15	**1.38E-12**	1.27E-14
Cropland	minimal	5.97E-13	**7.67E-13**	1.21E-13	7.56E-15	**1.65E-12**	1.01E-14
	light	6.47E-13	**8.90E-13**	1.37E-13	9.60E-15	**2.10E-12**	1.15E-14
	intense	6.56E-13	**9.11E-13**	1.40E-13	9.96E-15	**2.18E-12**	1.18E-14
Urban construction	minimal	6.62E-13	**1.10E-12**	8.56E-14	1.29E-15	**2.81E-13**	1.29E-14
Ecoregion PA0433							
Pasture	minimal	5,81E-12	1,50E-12	1,90E-11	1,68E-11	**5,18E-10**	2,14E-13
Cropland	minimal	5,24E-12	9,23E-13	1,85E-11	2,01E-11	**6,20E-10**	2,32E-13
	light	6,02E-12	1,13E-12	1,98E-11	2,55E-11	**7,87E-10**	2,84E-13
	intense	6,16E-12	1,17E-12	2,01E-11	2,64E-11	**8,17E-10**	2,93E-13
Urban construction	minimal	6,43E-12	1,38E-12	1,77E-11	3,41E-12	**1,05E-10**	1,09E-13
	intense	7.88E-12	1.66E-12	2.23E-11	3.2E-11	**9.9E-10**	3.55E-13
Ecoregion PA1209							
Pasture	minimal	1,94E-12	1,81E-12	2,60E-12	1,86E-12	**7,55E-11**	4,79E-14
Crop	minimal	1,89E-12	1,55E-12	2,76E-12	2,11E-12	**8,56E-11**	4,81E-14
	light	2,02E-12	1,68E-12	2,77E-12	2,44E-12	**9,88E-11**	5,29E-14
	intense	2,04E-12	1,70E-12	2,77E-12	2,48E-12	**1,01E-10**	5,36E-14
Urban construction	minimal	2,07E-12	1,80E-12	2,76E-12	4,61E-13	**1,87E-11**	3,60E-14
Ecoregion PA1215							
Pasture	minimal	1,59E-12	1,20E-12	6,69E-12	1,83E-12	**2,48E-10**	7,09E-14
Crop	minimal	1,55E-12	1,10E-12	6,77E-12	2,08E-12	**2,81E-10**	7,53E-14
	light	1,65E-12	1,15E-12	6,79E-12	2,40E-12	**3,25E-10**	8,32E-14
	intense	1,66E-12	1,16E-12	6,79E-12	2,44E-12	**3,31E-10**	8,43E-14

Urban construction	minimal	1,66E-12	1,20E-12	6,75E-12	4,54E-13	**6,14E-11**	4,17E-14
Ecoregion NT0704							
Pasture	minimal	5,25E-12	7,31E-12	**7,96E-12**	8,20E-13	5,63E-12	1,09E-13
Crop	minimal	5,24E-12	7,31E-12	**7,96E-12**	9,29E-13	6,38E-12	1,09E-13
	light	5,25E-12	7,31E-12	**7,97E-12**	1,07E-12	**7,37E-12**	1,10E-13
	intense	5,25E-12	7,31E-12	**7,97E-12**	1,09E-12	**7,51E-12**	1,10E-13
Urban construction	minimal	5,23E-12	7,32E-12	**7,97E-12**	2,03E-13	1,39E-12	1,05E-13
Ecoregion PA0419							
Pasture	minimal	1.18E-12	1.18E-12	1.43E-13	2.15E-14	**1.83E-12**	1.7E-14
Crop	minimal	1.24E-12	7.6E-13	1.32E-13	2.57E-14	**2.19E-12**	1.4E-14
	light	1.35E-12	9.06E-13	1.62E-13	3.27E-14	**2.78E-12**	1.59E-14
	intense	1.37E-12	9.32E-13	1.67E-13	3.39E-14	**2.89E-12**	1.63E-14
Urban construction	minimal	1.41E-12	1.18E-12	6.4E-14	4.37E-15	**3.73E-13**	1.79E-14
Ecoregion IM0160							
Pasture	minimal	1.54E-11	2.8E-11	1.01E-11	6.1E-12	**1.5E-10**	3.78E-13
Crop	minimal	1.29E-11	2.47E-11	1E-11	7.25E-12	**1.79E-10**	3.45E-13
	light	1.36E-11	2.56E-11	1.01E-11	9.13E-12	**2.25E-10**	3.7E-13
	intense	1.37E-11	2.58E-11	1.01E-11	9.45E-12	**2.33E-10**	3.75E-13
Urban construction	minimal	1.5E-11	2.74E-11	1E-11	1.26E-12	**3.11E-11**	3.37E-13

Table C-5. Characterization factors in PDF/m^2 for relevant ecoregions from Kuipers et al. (2021). Land use types include: U = urban, C = cropland, P = pasture, F = forestry, NA= Not available.

	Amphibians				Birds				Mammals				Reptiles				Aggregated			
Ecoregion	**U**	**C**	**P**	**F**	**U**	**C**	**P**	**F**	**U**	**C**	**P**	**F**	**U**	**C**	**P**	**F**	**U**	**C**	**P**	**F**
East European Forest steppe	6.71E-18	6.71E-18	NA	1.34E-17	2.71E-16	1.95E-16	NA	2.87E-16	1.00E-15	7.08E-16	NA	9.22E-16	2.40E-17	1.89E-17	NA	2.02E-17	3.26E-16	2.32E-16	NA	3.11E-16
Cerrado	2.80E-15	2.89E-15	2.39E-15	2.88E-15	4.21E-15	4.05E-15	3.97E-15	4.10E-15	4.06E-15	3.84E-15	3.84E-15	3.87E-15	1.05E-15	1.04E-15	1.05E-15	1.05E-15	3.03E-15	2.96E-15	2.81E-15	2.97E-15
Northeastern Spain and Southern France Mediterranean forests	4.37E-15	4.13E-15	NA	NA	9.58E-16	7.52E-16	NA	NA	1.45E-15	1.04E-15	NA	NA	5.45E-15	3.87E-15	NA	NA	3.06E-15	2.45E-15	NA	NA
Pyrenees conifer and mixed forests	NA	5.25E-15	5.25E-15	NA	NA	1.01E-17	1.25E-17	NA	NA	9.39E-16	6.61E-16	NA	NA	0.00E+00	0.00E+00	NA	NA	1.55E-15	1.48E-15	NA
Central forest-grasslands transition	4.61E-16	4.51E-16	4.29E-16	NA	6.76E-16	6.51E-16	6.69E-16	NA	8.27E-16	6.70E-16	6.70E-16	NA	1.08E-15	1.14E-15	9.50E-16	NA	7.61E-16	7.27E-16	6.79E-16	NA
Sarmatic mixed forests	2.56E-17	2.56E-17	2.56E-17	4.39E-17	1.93E-16	1.46E-16	1.75E-16	2.08E-16	4.09E-16	2.86E-16	1.91E-16	3.75E-16	1.52E-17	1.30E-17	1.09E-17	1.52E-17	1.61E-16	1.18E-16	1.00E-16	1.61E-16
Scandinavian and Russian taiga	2.02E-17	2.02E-17	2.02E-17	3.23E-17	3.53E-16	2.70E-16	3.21E-16	3.78E-16	4.87E-16	3.71E-16	2.86E-16	4.33E-16	1.45E-17	1.21E-17	9.69E-18	1.45E-17	2.19E-16	1.68E-16	1.59E-16	2.14E-16
Southern Great Lakes forests	6.17E-16	6.17E-16	6.37E-16	6.58E-16	7.81E-16	7.77E-16	7.77E-16	8.76E-16	4.95E-16	3.68E-16	3.58E-16	4.32E-16	9.43E-16	1.04E-15	7.86E-16	1.01E-15	7.09E-16	7.00E-16	6.39E-16	7.43E-16

Maputaland coastal forest mosaic	3.99 E-15	2.28 E-15	2.39 E-15	4.44 E-15	4.30 E-15	3.68 E-15	4.35 E-15	4.26 E-15	6.94 E-15	6.06 E-15	6.72 E-15	6.13 E-15	3.04 E-15	2.98E-15	2.98E-15	3.01 E-15	4.56 E-15	3.75 E-15	4.11 E-15	4.46 E-15
Upper Gangetic Plains moist deciduous forests	2.02 E-16	1.34 E-16	NA	NA	1.01 E-15	7.47 E-16	NA	NA	2.56 E-15	1.77 E-15	NA	NA	4.95 E-16	4.51E-16	NA	NA	1.07 E-15	7.75 E-16	NA	NA
Central American dry forests	4.21 E-15	4.50 E-15	4.06 E-15	NA	2.69 E-15	2.66 E-15	2.55 E-15	NA	1.06 E-15	9.45 E-16	9.97 E-16	NA	5.66 E-15	5.17E-15	4.74E-15	NA	3.40 E-15	3.32 E-15	3.09 E-15	NA
Northwestern thorn scrub forests	4.07 E-17	4.07 E-17	4.75 E-17	NA	1.99 E-15	1.55 E-15	2.02 E-15	NA	1.05 E-15	7.47 E-16	7.60 E-16	NA	1.92 E-15	1.90E-15	1.92E-15	NA	1.25 E-15	1.06 E-15	1.19 E-15	NA
Sahelian Acacia savanna	1.35 E-16	9.62 E-17	NA	1.25 E-16	2.07 E-15	1.62 E-15	NA	2.11 E-15	2.41 E-15	1.85 E-15	NA	2.33 E-15	6.22 E-16	5.94E-16	NA	6.11 E-16	1.31 E-15	1.04 E-15	NA	1.30 E-15
Sumatran peat swamp forests	2.45 E-15	2.45 E-15	NA	NA	8.40 E-15	7.71 E-15	NA	NA	9.07 E-15	7.67 E-15	NA	NA	7.39 E-15	7.27E-15	NA	NA	6.83 E-15	6.27 E-15	NA	NA

Table C-6. Characterization factors in units PDF/m2 from Knudsen et al. (2017)

Biome	Arable Crop organic intensive	Arable Crop organic extensive	Arable Crop conventional intensive	Arable Crop conventional extensive	pasture organic intensive	pasture organic extensive	pasture conventional intense	pasture conventional extensive
Temperate Broadleaf & Mixed Forests	0.29	0.203333333	0.68	0.336666667	-0.09	-0.42	0.1	-0.28

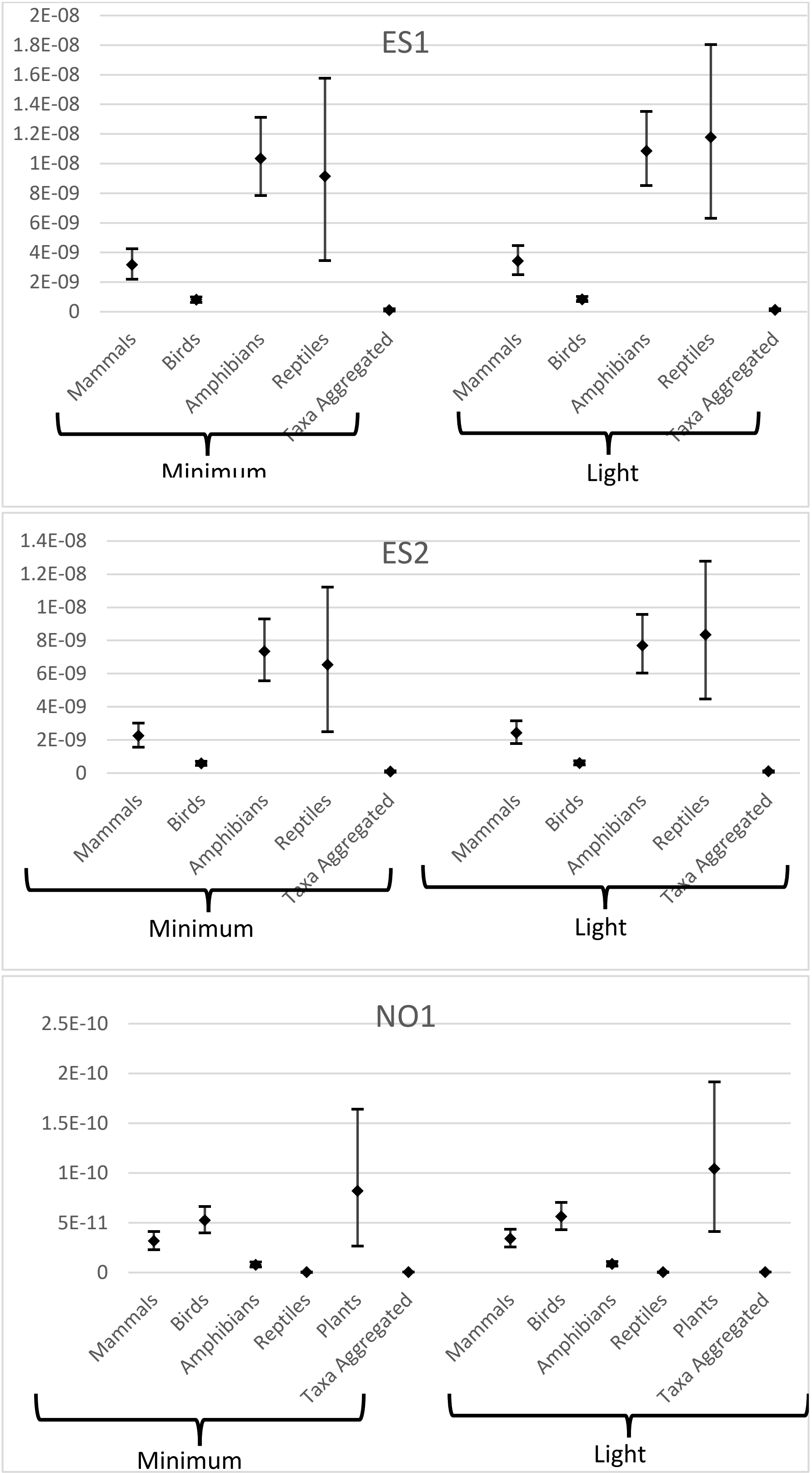
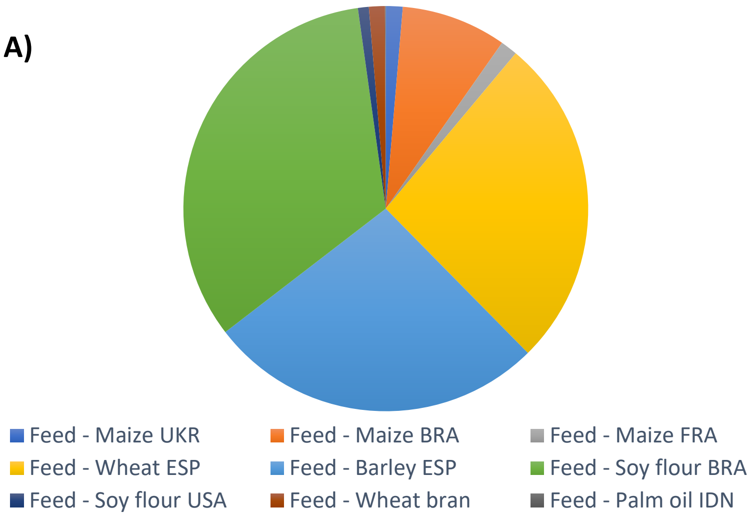
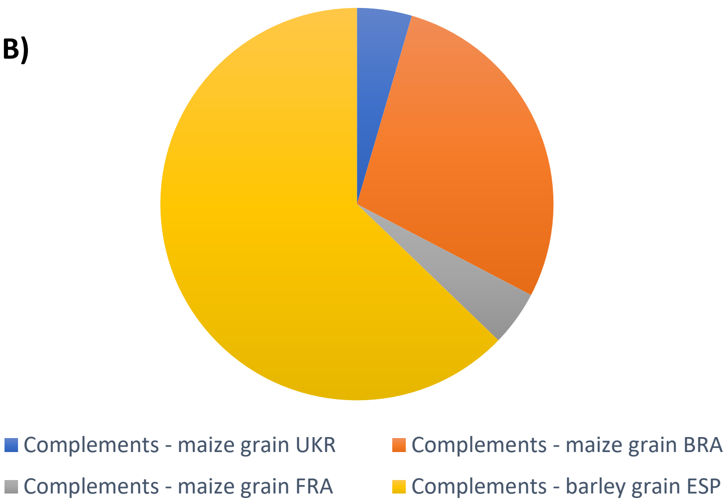


Figure C-1. Potential disappeared fraction (PDF) of species due to land use in case studies ES1, ES2 and NO1, showing sensitivity of intensity class on impact scores.

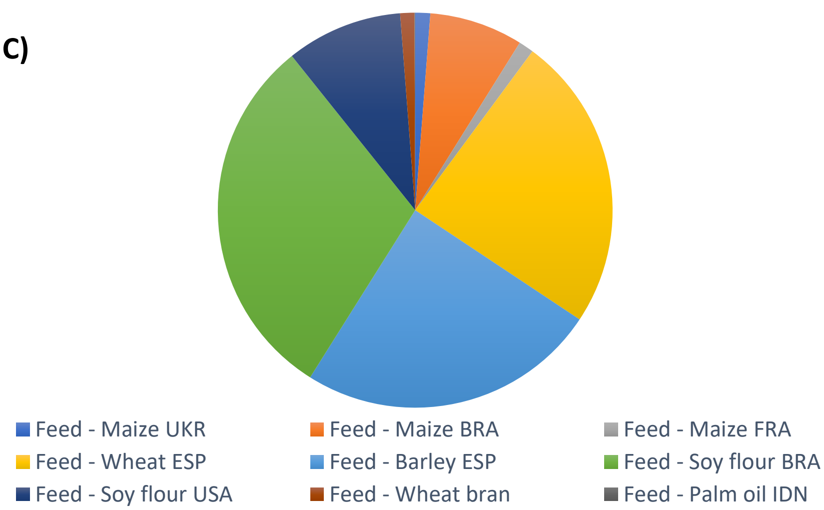
A)


Feed - Maize UKR
Feed - Maize BRA
Feed - Maize FRA
Feed - Wheat ESP
Feed - Barley ESP
Feed - Soy flour BRA
Feed - Soy flour USA
Feed - Wheat bran
Feed - Palm oil IDN

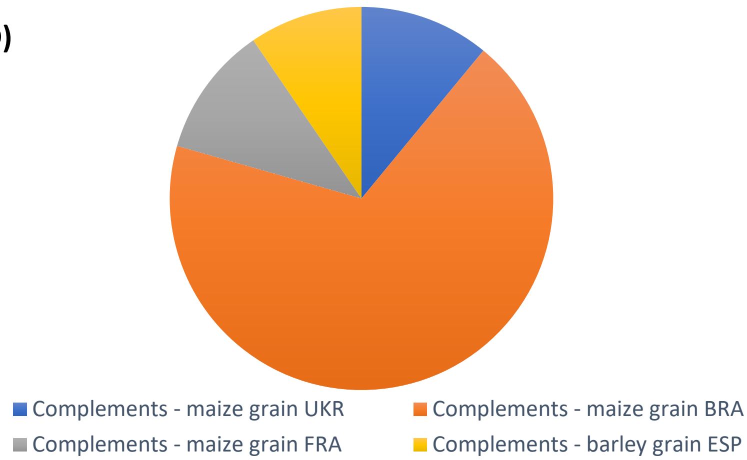
B)


Complements - maize grain UKR
Complements - maize grain BRA
Complements - maize grain FRA
Complements - barley grain ESP

C)


Feed - Maize UKR
Feed - Maize BRA
Feed - Maize FRA
Feed - Wheat ESP
Feed - Barley ESP
Feed - Soy flour BRA
Feed - Soy flour USA
Feed - Wheat bran
Feed - Palm oil IDN

D)



E)

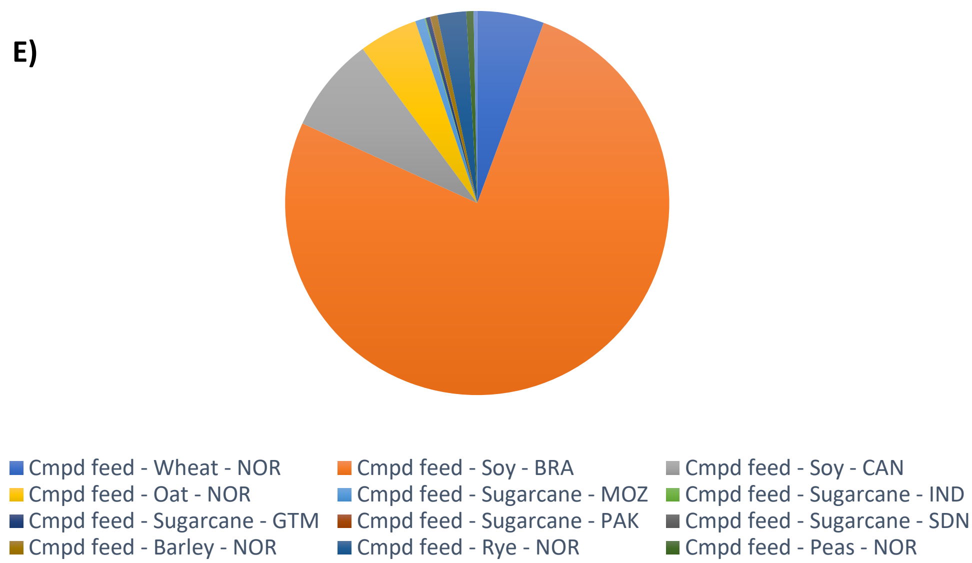
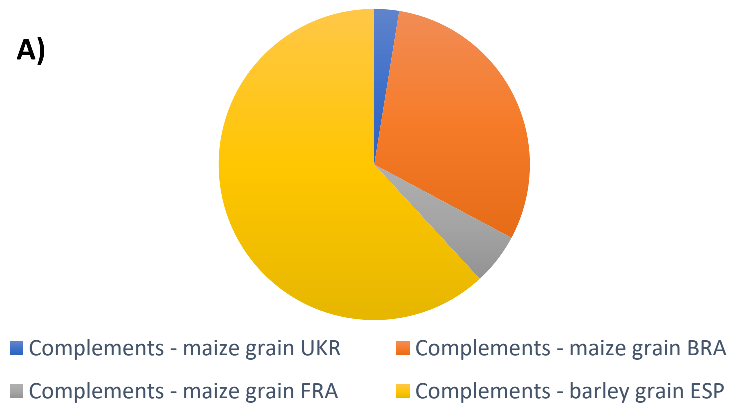
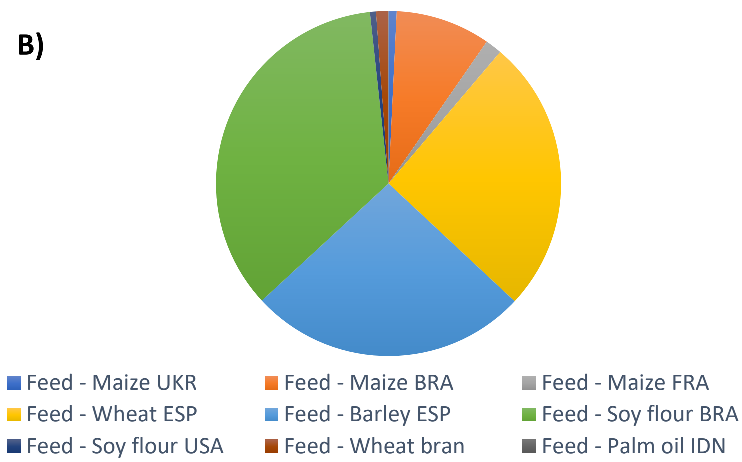


Figure C-2. Contribution of different land uses to total aggregated mean potential species loss in sheep farms using the model by Chaudhary and Brooks (2018) in case studies ES1 (A, fattening feed, B complementary feed), ES2 (C, fattening feed, D complements) and in NO1 (E).

A)


Complements - maize grain UKR
Complements - maize grain BRA
Complements - maize grain FRA
Complements - barley grain ESP

B)


Feed - Maize UKR
Feed - Maize BRA
Feed - Maize FRA
Feed - Wheat ESP
Feed - Barley ESP
Feed - Soy flour BRA
Feed - Soy flour USA
Feed - Wheat bran
Feed - Palm oil IDN

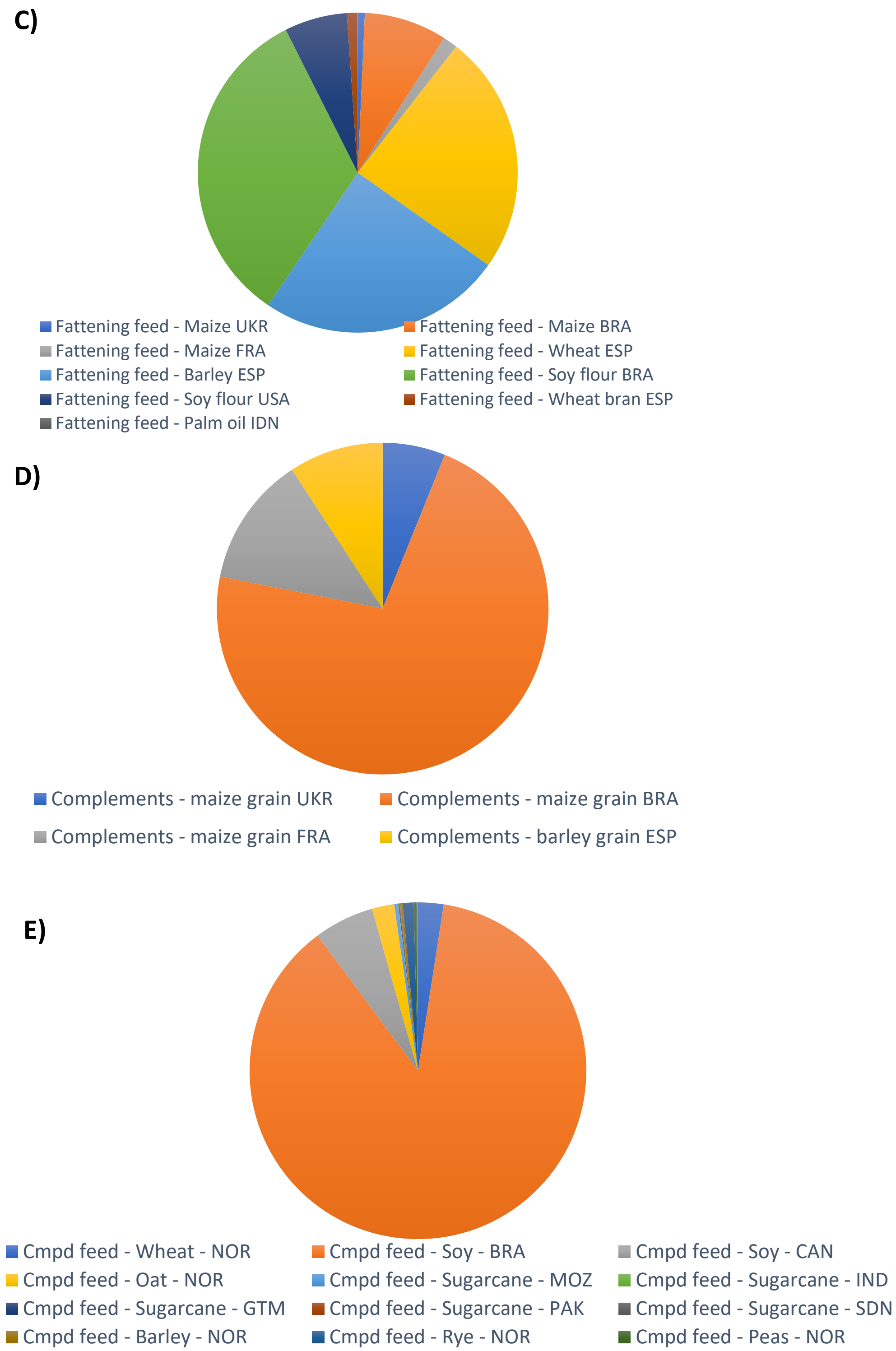


Figure C-3. Contribution of different land uses to total aggregated mean potential species loss in sheep farms using the model by Kuipers et al. (2021) in case studies ES1 (A, fattening feed, B complementary feed), ES2 (C, fattening feed, D complements) and in NO1 (E).

D. APPENDIX

Table D-1. Land management data derived from Lüscher et al. (2016) for organic and conventional farms in Spain, France and Italy, for olives, cereals and vineyards in those respective countries.

	Farm No.	Mean total nitrogen input (kg/ha)	Mean mineral nitrogen input (kg/ha)	Number of pesticide applications (No./ha)	Number of herbicide applications (No./ha)	Number of fungicide applications (No./ha)	Number of insecticide applications (No./ha)	Number of mechanical field operations (No./ha)
SPAIN (OLIVES, other woody crops)	**ORGANIC**							
	EO01	113	0	0	0	0	0	3.5
	EO02	46	0	0	0	0	0	2.9
	EO03	15	0	0	0	0	0	2.9
	EO04	40	0	1	0	1	0	5
	EO05	23	0	2	0	2	0	5
	EO06	80	0	0.9	0	0.9	0	2.8
	EO07	16	0	0.9	0	0	0	5.7
	EO08	140	0	0	0	0	0	0.9
	EO09	88	0	0	0	0	0	2.2
	EO10	134	0	2	0	2	0	9
	Mean	*69.5*	*0*	*0.7*	*0*	*0.6*	*0*	*3.9*
	Standard deviation	*48.2*	*0*	*0.8*	*0*	*0.8*	*0*	*2.3*
	CONVENTIONAL							
	EO11	38	37	1	0	1	0	5.7
	EO12	32	32	0.9	0	0.9	0	3.7
	EO13	30	30	1	0	1	0	6
	EO14	75	29	1	0	1	0	6
	EO15	32	32	0	0	0	0	2
	EO16	16	9	0	0	0	0	1.9
	EO17	147	39	0	0	0	0	4

	EO18	59	32	1	0	1	0	5.8
	EO19	40	40	0	0	0	0	3
	EO20	71	29	0	0	0	0	2.7
	Mean	*54*	*30.9*	*0.5*	*0*	*0.5*	*0*	*4.1*
	Standard deviation	*37.8*	*8.7*	*0.5*	*0*	*0.5*	*0*	*1.7*
FRANCE (Wheat & Barley)	**ORGANIC**							
	FR03	74	74	4.2	2	1.2	1	11.4
	FR06	81	81	2.1	1	0	0.3	5.6
	FR07	93	66	2.2	2.2	0	0	6.8
	FR08	125	45	0.6	0.6	0	0	6.9
	FR09	126	126	3.9	2.9	1	0	10.8
	FR11	135	99	1.6	0.4	0.9	0.3	7.7
	FR12	183	41	3.3	3	0	0.2	6.2
	FR15	91	1	3	1.7	1.3	0	9.9
	Mean	*113.5*	*66.6*	*2.6*	*1.7*	*0.5*	*0.2*	*8.2*
	Standard deviation	*36.1*	*38.3*	*1.2*	*0.9*	*0.6*	*0.3*	*2.2*
	CONVENTIONAL							
	FR01	37	0	0	0	0	0	4.9
	FR02	44	0	0	0	0	0	4
	FR04	34	0	0	0	0	0	7
	FR05	62	0	0	0	0	0	6
	FR10	18	0	0	0	0	0	5.1
	FR13	71	0	0	0	0	0	5.6
	FR14	55	0	0	0	0	0	6.7
	FR16	28	0	0	0	0	0	3.8
	Mean	*43.6*	*0*	*0*	*0*	*0*	*0*	*5.4*
	Standard deviation	*17.9*	*0*	*0*	*0*	*0*	*0*	*1.2*

ITALY (Vineyards)	**ORGANIC**							
	IT01	8	0	26	0	17	9	29
	IT03	6	0	22	0	22	0	26
	IT05	20	0	21	0	17	4	26
	IT07	1	0	12	0	6	6	20.5
	IT09	10	0	8.6	0	8.6	0	12.4
	IT11	5	0	13.9	0	11.1	2.8	18.7
	IT13	0	0	13	0	13	0	17
	IT15	49	0	16	0	13	2	21
	IT17	38	0	35.8	0	17.5	18.3	39.4
	Mean	*15.2*	*0*	*17.2*	*0*	*12.3*	*4.7*	*22.1*
	Standard deviation	*17.3*	*0*	*9.0*	*0*	*4.2*	*6.3*	*8.7*
	CONVENTIONAL							
	IT02	101	80	12.2	1	10.3	0.9	18
	IT04	51	51	13	0	10	3	17
	IT06	32	32	26	4	20	2	32
	IT08	0	0	13	1	10	2	18
	IT10	44	44	20	2	18	0	25
	IT12	11	0	11.7	1.9	8.8	1	16.7
	IT14	35	35	12.1	2.8	9.2	0.1	15.9
	IT16	0	0	20.8	3.9	15.9	0.9	26.8
	IT18	3	0	17.8	0	14.2	3.7	19.8
	Mean	*30.8*	*26.9*	*16.3*	*1.8*	*12.9*	*1.5*	*21.0*
	Standard deviation	*32.7*	*28.9*	*5.1*	*1.5*	*4.2*	*1.3*	*5.6*