Thèse n° 9688

Regionalized Life Cycle Assessment of Food and Energy Systems

Présentée le 7 mars 2022

Faculté des sciences et techniques de l'ingénieur
Groupe SCI STI FM
Programme doctoral en énergie

pour l'obtention du grade de Docteur ès Sciences

par

Xun LIAO

Acceptée sur proposition du jury

Dr J. Van Herle, président du jury
Prof. F. Maréchal, Prof. M. D. Margni, directeurs de thèse
Prof. M. Hauschild, rapporteur
Dr E. Benetto, rapporteur
Dr C. Mutel, rapporteur

École
polytechnique
fédérale
de Lausanne

2022

Acknowledgement

It has been a long marathon for me to finish this thesis. During this journey, I moved from Boston to Switzerland. My girlfriend is now my wife. And we have our new member into our family, little Xena. Our angel baby is now 7-month-old!

I would like to thank my supervisor, Francois Marechal, and my co-supervisor, Manuele Margni, for the support, advice, and inspiring discussions to complete this thesis.

I sincerely appreciate the jury members, Professor Michael Hauschild, Dr. Enrico Benetto and Dr. Chris Mutel, for being part of the jury committee to support.

I want to give special thanks to my colleagues in Quantis Lausanne and the many people I have collaborated with through the UNEP-SETAC Life cycle initiative and European research projects.

My deepest gratitude goes to my parents, Xiuying Wu and Jianhua Liao, and my wife Sarah (Dan Xu) who have been supporting me all along the way.

Morges, February 9, 2022

Abstract

To steer the sustainable transition in the food and energy sectors, reliable environmental data is required to answer environmental questions related to single agricultural crop, food product or energy technologies. Life cycle assessment (LCA) has been widely applied to assess the environmental footprints and mitigation potentials of a product. Given the large spatial variabilities of food and electricity production, regionalized LCA is regarded to provide more accurate environmental impact.

When the sourcing country of production origin for a purchased product is unknown, a process-based regionalized LCA is often conducted arbitrarily with subjective choices of estimating sourcing countries of production origins. This thesis developed a general process-based regionalized LCA computational structure to improve the inclusion of spatial details of tracing the spatial locations of cross-border product flows from origin of production to destination of consumption, based on the commodity balancing of a product on the country level. The model is validated with a numerical example and demonstrated with a case study from literature for an improved accuracy of impact results. The proposed model offers a coherent and transparent way of analyzing the influence of different trade assumptions or truncation errors. It can be used to improve the global value chain modeling of agricultural commodities.

Increasingly, companies are making product footprint and comparative claims available on the individual product level. International food companies often have a global footprint in their product supply chain and a large product portfolio for the same functionality sold in various consumer markets. This thesis developed a stepwise framework for operationalizing the application of regionalized LCA to assess a large-scale portfolio of food product. Its feasibility and reliability are tested with a case study comparing 212 plant-based fat spreads and 40 dairy butters sold in 21 countries. It shows large inter-product variabilities, ranging from 0.98 to 6.93 (mean 3.3) kg CO_2-eq/kg for 212 plant-based spreads and 8.08 to 16.93 (mean 12.1) kg CO_2-eq for 21 dairy butters. The key drivers and main uncertainties of impact are the assumptions of the sourcing country of production and GHG emission from land use change.

This thesis further assessed the influence of different regionalized LCA model assumptions and temporal resolutions on the carbon footprint of power to gas (PtG) applications. When the electricity input is based on a renewable electricity mix with guarantee of origin, PtG under study have a 32-65% reduction of carbon footprint compared to fossil natural gas. With current national average consumption mix on a yearly basis, PtG production in Switzerland could be operated to provide climate benefits. However, when moving from yearly average to hourly resolution, PtG has a higher carbon footprint for more than 50% of

time over the year. Thus, the deployment of PtG should be guided in a finer temporal resolution to gain potential climate benefits.

The regionalized LCA model and methodology as well as case studies contribute to advance our understanding in the methodological aspect of regionalized LCA model and key issues related to its practical operationalization and applications.

Keywords: Life cycle assessment, spatiotemporal differentiation, regionalization, global value chain, agricultural commodities, dietary choice, power to gas, carbon footprint

Résumé

Pour piloter la transition durable dans les secteurs de l'alimentation et de l'énergie, des données environnementales fiables sont nécessaires pour répondre aux questions environnementales liées à une seule culture agricole, un seul produit alimentaire ou une seule technologie énergétique. L'analyse du cycle de vie (ACV) a été largement appliquée pour évaluer les empreintes environnementales et les possibilités d'atténuation d'un produit. Étant donné les grandes variations spatiales de la production alimentaire et électrique, les ACV régionalisées sont considérées comme fournissant un impact environnemental plus précis.

Lorsque le pays d'origine de la production d'un produit acheté est inconnu, une ACV régionalisée basée sur les processus est souvent menée de manière arbitraire avec des choix subjectifs d'estimation des pays d'origine de la production. Cette thèse a développé une structure de calcul d'ACV régionalisée basée sur les processus afin d'améliorer l'inclusion des détails spatiaux de traçage des flux de produits transfrontaliers depuis l'origine de la production jusqu'à la destination de la consommation, sur la base de l'équilibrage des produits de base d'un produit au niveau national. Le modèle est validé par un exemple numérique et démontré par une étude de cas tirée de la littérature pour une meilleure précision des résultats de l'impact. Le modèle proposé offre un moyen cohérent et transparent d'analyser l'influence de différentes hypothèses commerciales ou d'erreurs de troncature. Il peut être utilisé pour améliorer la modélisation de la chaîne de valeur mondiale des produits agricoles de base.

De plus en plus, les entreprises rendent disponibles l'empreinte des produits et les allégations comparatives au niveau des produits individuels. Les entreprises alimentaires internationales ont souvent une empreinte globale dans leur chaîne d'approvisionnement et un large portefeuille de produits pour la même fonctionnalité vendus sur différents marchés de consommation. Cette thèse a développé un cadre par étapes pour rendre opérationnelle l'application de l'ACV régionalisée pour évaluer un portefeuille de produits alimentaires à grande échelle. Sa faisabilité et sa fiabilité sont testées par une étude de cas comparant 212 matières grasses à tartiner d'origine végétale et 40 beurres laitiers vendus dans 21 pays. Elle montre de grandes variabilités inter-produits, allant de 0,98 à 6,93 (moyenne 3,3) kg d'éq. CO2/kg pour 212 matières grasses à tartiner d'origine végétale et de 8,08 à 16,93 (moyenne 12,1) kg d'éq. CO2 pour 21 beurres laitiers. Les principaux facteurs et les principales incertitudes de l'impact sont les hypothèses du pays d'origine de la production et l'émission de GES due au changement d'affectation des terres.

Cette thèse a également évalué l'influence de différentes hypothèses de modèles ACV régionalisés et de résolutions temporelles sur l'empreinte carbone des applications Power to Gas (PtG). Lorsque la consommation d'électricité est basée sur un mélange d'électricité renouvelable avec une garantie d'origine, le PtG étudié a une réduction de 32-65% de l'empreinte carbone par rapport au gaz naturel fossile. Avec le mix de consommation national moyen actuel sur une base annuelle, la production de PtG en Suisse pourrait être exploitée de manière à fournir des avantages climatiques. Cependant, en passant de la moyenne annuelle à la résolution horaire, le gaz de pétrole liquéfié a une empreinte carbone plus élevée pendant plus de 50 % du temps au cours de l'année. Ainsi, le déploiement du PtG devrait être guidé dans une résolution temporelle plus fine pour obtenir des bénéfices climatiques potentiels.

Le modèle ACV régionalisé et la méthodologie ainsi que les études de cas contribuent à améliorer notre compréhension de l'aspect méthodologique du modèle ACV régionalisé et des questions clés liées à son opérationnalisation et ses applications pratiques.

Mots-clés: Analyse du cycle de vie, différenciation spatio-temporelle, régionalisation, chaîne de valeur mondiale, produits agricoles de base, choix alimentaire, passage de l'électricité au gaz, empreinte carbone.

Table of Contents

Abbreviation

AWARE	The available water remaining
CF	Characterization Factors
EC	European Commission
EEIOA	Environmentally extended input-output analysis
EW	Economy wide
FAO	Food and Agriculture Organization
FU	Functional unit
GHGs	Greenhouse gases
GVC	Global value chain
GWP	Global warming potentials
IRIO	Interregional input-output
ISO	International standard organization
IOA	Input output analysis
LCA	Life cycle assessment
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
LUC	Land use change
MFA	Material Flow Analysis
MRIO	Multi-regional input-output
NTP	Normal Temperature and Pressure
PEFCR	Product Environmental Footprint Category Rules
PEM	Polymer electrolyte membrane
PtG	Power to Gas
PtH	Power to hydrogen
PtM	Power to methane
PV	Photovoltaics
RES	Renewable energy sources
RLCA	Regionalized Life Cycle Assessment
SETAC	Society of Environmental Toxicology and Chemistry
SNG	Synthetic natural gas
UNEP	The United Nations Environment Programme
VRE	Variable renewable electricity
WF	Water footprint
WSI	Water scarcity index

List of Figures

List of Tables

Symbol

symbol	Explanation
$\boldsymbol{i}$	commodity index
$\boldsymbol{j}$	activity index
$\boldsymbol{A}$	technology matrix, product by activity ($n \times n$)
$\boldsymbol{B}$	environmental flow matrix, environmental flow by activity ($m \times n$)
$\mathbf{V}'$	supply matrix, part of the technology matrix ($n \times n$)
$\mathbf{U}$	use matrix, part of the technology matrix ($n \times n$)
$\boldsymbol{f}$	functional unit, vectors of commodities ($n \times 1$)
$\boldsymbol{G}$	matrix of environmental flows associated with each functional unit ($m \times n$)
$\boldsymbol{g}$	vector of environmental flows associated with a functional unit ($m \times 1$)
$\boldsymbol{C}$	characterization matrix, impact indicators by environmental flows ($l \times m$)
$\boldsymbol{H}$	Matrix of impact results of for all indicators and processes ($l \times$ n)

1 Introduction

1.1 The context of sustainability transition in the food and energy sectors

Human activities have led to climate change, looming land scarcity and water scarcity (Lambin and Meyfroidt 2011; Schutter 2011; Meyfroidt et al. 2013; Friis and Nielsen 2019) (Mekonnen and Hoekstra 2016). According to the IPCC report published in 2018 (Rogelj et al. 2018), the remaining carbon budget is less than 420Gt CO_2 or 10 years of current emissions if we want to stay below the 1.5°C threshold. To deal with the climate emergency (Ripple et al. 2019; Gills and Morgan 2020), many countries, companies, and organizations have pledged to reach carbon neutrality or science-based reduction targets (Flagg 2015; Faria and Labutong 2019; Walenta 2020). To achieve the 1.5°C target, it would require large-scale transformations of the global energy–agriculture–land-economy system, affecting the way in which energy is produced, agricultural systems are organized, and food, energy and materials are consumed (Clarke et al. 2015). From the sectoral perspective, agriculture, food and energy sectors are responsible for majority of the global greenhouse gases (GHG) emissions, land occupation and freshwater consumption (Ritchie and Roser 2013, 2017a, b, 2020). To achieve the 1.5°C pathways, the main sectoral mitigation strategies includes but not limited to: i) "demand-side measures such as lifestyle choices lowering energy demand and the land- and GHG-intensity of food consumption (high confidence)"; ii) "environmentally oriented technological development, such as greater deployment of renewable energy (RE) and addressing integration needs in the power sector and switching to low-carbon fuels (electricity, hydrogen, and so forth) for industry, building and transport" (IPCC 2014; Field et al. 2014; Rogelj et al. 2018). For the latter, a promising solution is the emerging Power-to-Gas (PtG) technologies that combine the hydrogen generated from low carbon electricity and captured CO_2 (Zeman and Keith 2008).

- **The role of dietary change to enable sustainable food transition**

Food production is estimated to be responsible for up to 30% of global greenhouse gas emissions (Vermeulen et al. 2012). Replacing animal-based food sources by plant-based alternatives could be a way to reduce the current impact of food production and consumption

(Ranganathan et al. 2016; Poore et al. 2018; Willett et al. 2019). Poore and Nemecek (2018) argues dietary change by consumers can deliver environmental benefits on a scale not achievable by producers.

- **The role of Power to Gas to enable sustainable energy transition**

Variable renewable energy sources (VRE), such as wind and solar, have the technical potentials to supply the global energy demand (Jacobson and Delucchi 2011) to abate carbon emissions. However, the VRE and its availability are unevenly distributed across different periods and regions, resulting in the imbalance of supply and demand across different time scales (daily and seasonal periods) and grid instability. Incorporating energy storage technologies along with VRE deployment towards energy transitions is thus indispensable for achieving high penetration of renewable electricity. The German energy transition experience shows that the focus of decarbonization of electrical grids alone is not sufficient for meeting the decarbonization target if not connecting the renewable power sector with industry, transport, and heat/cooling demand, termed as "sector coupling" (Brown et al. 2016; Blanco and Faaij 2018). Among existing energy storage technologies (Luo et al. 2015), PtG is regarded as a promising bridging technology for long-term seasonal energy storage by producing hydrogen and synthetic natural gas (SNG) (Moore and Shabani 2016; Blanco and Faaij 2018) and is the key enabler for sector coupling that connects renewable energy with transportation, heat and industry (Michalski et al. 2017; Buttler and Spliethoff 2018; Robinius et al. 2017).

1.2 LCA as a tool to steer the sustainable transition

To steer the sustainable transition in the food and energy sectors, reliable environmental data is required to answer the following questions:

1) On the single commodity level (agricultural crops or electricity), how companies or organizations can calculate accurately the environmental impacts for commodities from producers in different regions to consumers around the world within a complex globalized or regional supply chain?
2) One the product level (such as animal-based food or plant-based alternatives), how companies can design more environmentally friendly dietary choices considering different recipe ingredients, sourcing difference, processing and logistics, and communicate robust environmental footprint information to inform consumer dietary change?

3) On the technological development level (such as power-to-gas), how to accurately assess the environmental performance of emerging innovative energy technologies to inform policymakers for promoting the environmentally friendly technology development?

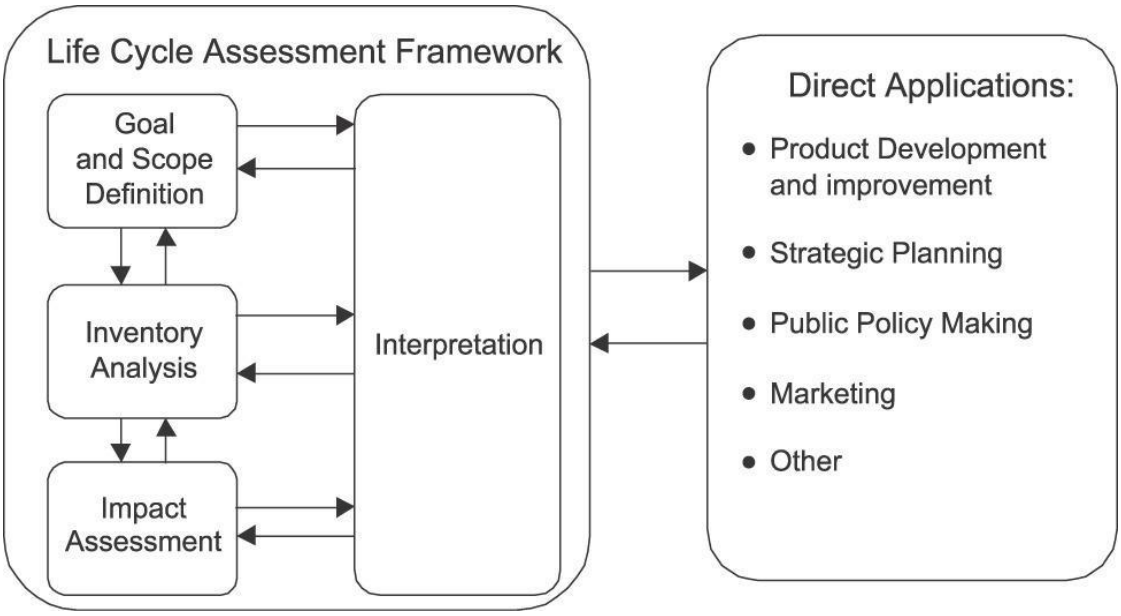

Figure 1.1 The framework of LCA and direct applications for decision-support. Reprinted from (Rebitzer et al. 2004)

Life cycle assessment (LCA), a science-based approach as shown in Figure 1.1, has been widely applied in industry, research and policy decision-making to assess and evaluate the environmental footprints and mitigation potentials of product or service from different organizational levels (from product-level, firm-level, to sector-wide, city and nation-wide) to support business strategy, eco-design, product or brand communication and policy decision makings (Hellweg and Milà i Canals 2014; Hoekstra and Wiedmann 2014; Poore and Nemecek 2018; Willett et al. 2019). Based on a measurable functional unit, the LCA approach has a complete system boundary from cradle to grave to assess multiple environmental indicators associated with all stages of a product's life cycle from raw material extraction to production, use and end of life. It takes a holistic systematic perspective including all value chains and relevant environmental impact categories to avoid problem shifting from one environmental issue (e.g., climate change) to another (e.g., water scarcity, land use and biodiversity) or from one production stage or geographical region to another.

1.3 State of the art of LCA and its applications in assessing food and energy

Recent advances in LCA shows that not only the life cycle impact assessment (LCIA) characterization factors (CFs) could be sensitive to locations, for example, water scarcity (Boulay et al. 2017) and biodiversity impact (Chaudhary et al. 2016), technology coefficients

of producing the same product is also not homogeneous across regions when it comes to electricity production (Mutel, et al. 2009) and agricultural commodities (Pfister et al. 2009; Peano et al. 2012a; Nemecek et al. 2015; Durlinger et al. 2014; Poore and Nemecek 2018; Chaudhary et al. 2016). Towards more accurate quantification of environmental impact of food and electricity-derived energy product, regionalized LCA is needed (Hellweg and Milà i Canals 2014). Furthermore, the temporal differentiation becomes relevant when assessing variable renewable electricity production (Vuarnoz and Jusselme 2018; Messagie et al. 2014).

In the past decade, one of the key developments in the field of LCA is moving from site-generic LCA to spatially differentiated regionalized LCA assessment (Hellweg and Milà i Canals 2014). However, it is not a trivial task with a complex supply chain. Figure 1.2 illustrates the multiple tiers of supply chain from producers to consumers. The geographical location of tier n supplier is where a product is produced. When consumers purchase commodities from a market mix pool, the exact producer and their sourcing spatial location is often unknown.

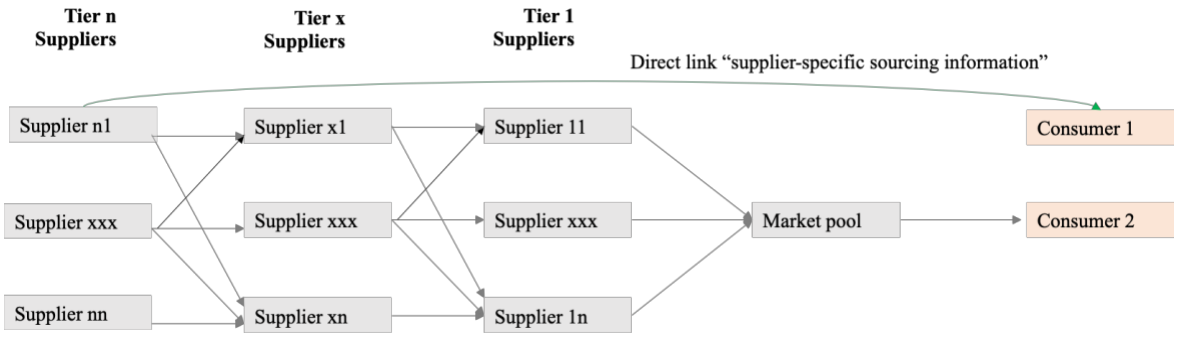

Figure 1.2 Multiple tiers of supply chain from producers to consumers

Figure 1.3 further illustrates the relationship of production and consumption following Lenzen et al. (2004)'s classifications:

a. Autonomous economy: there is no foreign trade, product technology is homogenous in that region.
b. Uni-directional trade: there is trade across regions, but it is uni-directional from one region to another.
c. Network trade: the trade is multi-directional in a global value chain. Each country is simultaneously trading with the rest of the world for various products.

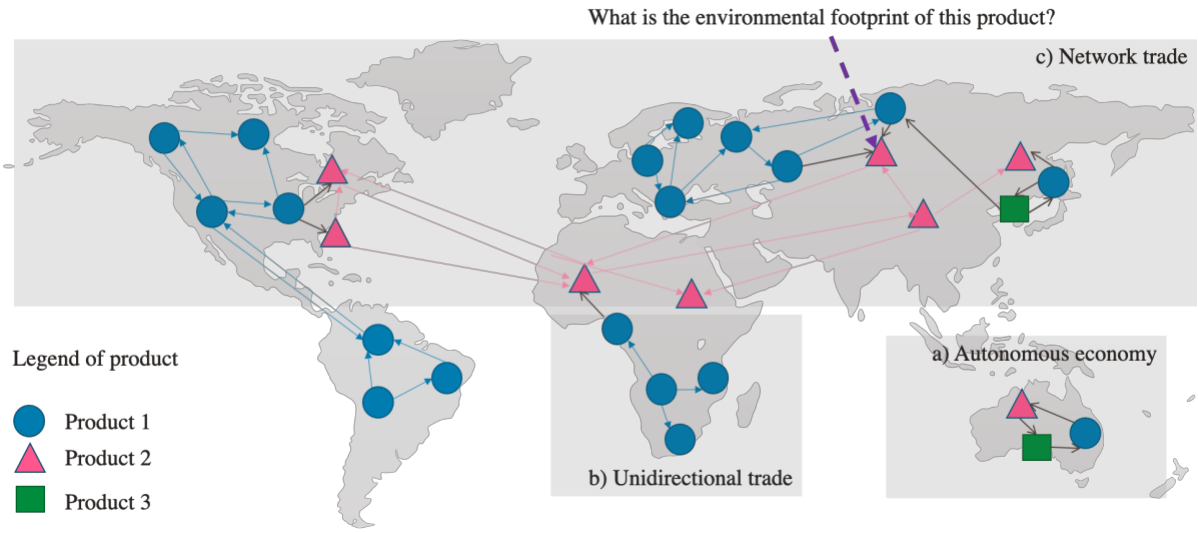

Figure 1.3 The complexity of global value chain of three inter-connected products

The actual situation is closer to the scenario c network trade. For example, to properly calculate the environmental impact of product 2 of the highlighted "red triangles" in a network trade situation, several aspects need to be addressed:

- **Inter-commodity relationship:** How to model the "inter-commodity" or "inter-industry" relationship? For example, Product 2 use product 1 as input, and product 2 is also used as input for product 1, creating "feedback loop". Product 1 also uses product 3 as input.
- **Spatial variability**: How to differentiate the production variability of different products among different regions? How to consider the sensitivity of environmental emissions to different local environment, for example the water scarcity is different with different locations?
- **Commodity flow tracing problem:** How to trace the actual commodity production origins from a trade network? This is termed as "commodity or product flow tracing problem". For example, the product 1 used by product 2 could come from the local production but also from other regions in the trade network.

Various efforts have been developed to address partially or fully of the aspects mentioned above, as discussed below:

- **Inter-commodity relationship**: Traditional process-based LCA approach includes the "inter-commodity" relationship in the technosphere matrix modeling inter-connected economic flows, but it suffers truncations errors due to incomplete inclusion of all

economic activities. The economic or hybrid multi-regional input-out (MRIO) approaches offers a comprehensive coverage of the interactions of different sectors for major economies with a more complete system boundaries to avoid truncation errors (Moran and Wood 2014; Wood et al. 2014, 2015; Merciai and Schmidt 2018; Stadler et al. 2018; Bjelle et al. 2020). However, it does not have the required high specificity on a product level.

- **Spatial variability**: The ecoinvent (2018) database provides spatially differentiated electricity grid mix and other products on a nation or sub-national level and regionalized water flows (Vionnet et al. 2012; Pfister et al. 2016). Spatial life cycle inventory (LCI) are also developed from various sectorial database, for example for textile and leather (Quantis 2018), agri-food products (Peano et al. 2012; Colomb et al. 2015; Durlinger et al. 2014), and forestry (Cardellini et al. 2018). The water footprint network (Hoekstra et al. 2014) provides spatially differentiated water flow for agricultural product production. For the spatial differentiation of the potential environmental impact, characterization models have been developed for different impact categories such as water use, biodiversity, acidification, and eutrophication impact (Pfister and Bayer 2014; Boulay et al. 2017; Levasseur et al. 2010; Brandão et al. 2013; Verones et al. 2017; Mutel et al. 2018; Huijbregts et al. 2016; Bulle et al. 2019; Verones et al. 2020; Chaudhary et al. 2016). See more review from (Mutel et al. 2018)
- **Commodity flow tracing problem:** it is to track the flow of product from production origins to destinations of consumption. Statistics (trade, production and consumption data) are used to model commodity flows; however, the modeling of sourcing country of production origin is challenging due to reimport and reexport activities. For example, the trade statistics shows a large portion of palm oil consumed in Switzerland is from Netherlands, however, Netherlands does not cultivate palm oil. Different approaches of handling trade data and flow tracing are discussed below:
    a. **Direct trade adjustment approximation.** This approach considers the traded product having the same environmental properties as the domestic product. See the definition in (Qu et al. 2017). It is widely applied in LCA studies, for example when the "net import or export volume" is used for LCA studies, it ignores the heterogeneity between the imported and exported product. A common approximation is to assume product production origin originates from

where the product is imported, however this is not necessarily the case, because often countries trade with multiple partners as shown in Figure 1.3 scenario c.

b. **The regional or global average approximation approach**. It assumes product consumed in different countries are proportional to the same characteristics of the average regional or global production or export share. Yang (2016) refers this as "regional output percentage (ROP)". This approach finds its applications in various commercial database, such as ecoinvent and World Food LCA Database (Bengoa et al. 2020).

c. **The tiered approximation** (own definition). It tracks the import and export data from trading partners beyond the first-tier suppliers. Rather than solving the network trade problem simultaneously, it also tracks tier 2 or even tier 3 trading partners to approximate the network modeling approach.

a. **Network modeling**. Kastner et al. (2011) developed a method to trace the agricultural commodity flow based on the Leontief demand approach with applications into estimating direct farm emission impact. Qu et al. (2017) illustrated the electricity flow tracing modeling with a Ghosh supply perspective to estimate direct combustion carbon emissions. Both methods are based on network trade modeling approach, which solves simultaneously the interconnected network trade as described in scenario c in Figure 1.3. However, this approach has not been fully integrated into the LCA computation models.

Beyond the model development, the application of LCA into food and energy are further elaborated in section 1.4 below.

1.4 Research gaps

1.4.1 Incorporating commodity flow tracing in process-based regionalized LCA

Although various work have been developed to define and guide one or more aspects of regionalized LCA analysis as discussed above and summarized in Table 1.1, none of them provide a computational framework in the perspective of process-based regionalized LCA to describe how to solve interconnected cross-border commodity flows tracing, representing the reality of the simultaneously trading network among industries from different national jurisdictions when the commodity production sourcing location is unknown, as further elaborated below:

- Ecoinvent (2018) has differentiated production datasets or "transformation activity" and market datasets that includes trade data; however it does not clarify how commodity flow tracing should be handled in the process-based regionalized LCA.
- The newly developed food related database WFLDB (Bengoa et al. 2020) provide either a country-specific production dataset or a global average mix; however, it does not provide the mapping from country of origins to country of consumptions for the agricultural commodities.
- Mutel et al. (2009) proposed a method to mapping spatial CFs with spatial elementary flows within the regionalized LCA computational structure. It is not targeted to address how the cross-border commodity flows tracing issue should be formulated in the regionalized LCAs.
- The economic multiregional input output (MRIO) is a top town approach at the sector level, without providing disaggregated information on the product/commodities (Moran and Wood 2014; Wood et al. 2014, 2015; Merciai and Schmidt 2018; Stadler et al. 2018; Bjelle et al. 2020). There are increasing effort to link MRIO database with conventional Process-based LCA database such to create a hybrid analysis to reduce the truncation of incomplete system boundaries, however, it does not address the problem at hand to solve the commodity flow tracing problem for a process-based regionalized LCA.
- Kastner et al. (2011) and Qu et al. (2017) both developed commodity flow tracing models flow with bilateral trade, production and consumption data from either the quasi-Leontief demand or the Ghosh supply perspective with applications to estimate direct emissions. However, their models are not developed and formulated in the process LCA computational structure to deal with the inter-commodity relationship, i.e., interactions of multiple products that uses each other as inputs in the technosphere matrix of a LCA (for example, electricity requires coal production and coal production requires electricity input).
- Yang et al. (2017) recently proposed computational frameworks for regionalized LCA used for product LCA analysis stemming from the MRIO framework, however it assumes the product country of origin/destination of consumption (OD) data is already known, without addressing specifically the commodity flow tracing challenge posed in this thesis.

Further in-depth literature review is provided in detail in Chapter 2 of this thesis.

Table 1.1 Overview of data and modeling approaches related to regionalized LCA components

Reference	Water [1] (Hoekstra et al. 2014)	Generic database ecoinvent (2018)	Sector database [2]	LCIA[3]	Mutel (2009)	EE-MRIO[4]	Kast-ner (2011)	Qu (2017)	Yang (2017)	This thesis
Applications	water	generic (G)	e.g. Food	various	grid mix	G	food	grid mix	G	G
1. Life cycle inventory										
1.1 Elementary flow	x	x	x		x	x	x	x	x	x
1.2 Economic flow: inter-commodity relationship	x	x	x		x	x			x	x
1.3 High level of details	x	x	x		x		x	x	x	x
1.4 Direct link or market average		x	x						x	x
2. LCIA characterization model										
2.1 Elementary flow				x	x	x			x	x
3. Commodity flow tracing models										
3.1 Direct trade adjustment proximation		x	x							x
3.2 Regional or global average proximation		x	x							x
3.3 Tiered proximation		x	x							x
3.4 Network modeling							x	x		x
3.5 Precalculated or known						x	x		x	
4. Global supply chain coverage for one or all products						x	x	x	x	x

[1] See more work towards regionalizing water flows (Vionnet et al. 2012 ; Pfister et al. 2016)
[2]Textile and leather (Quantis 2018 a, b), agri-food products (Peano et al. 2012; Colomb et al. 2015; Durlinger et al. 2014), forestry (Cardellini et al. 2018)
[3] See studies (Pfister and Bayer 2014 ; Boulay et al. 2017 ; Levasseur et al. 2010 ; Brandão et al. 2013 ;Verones et al. 2017 ; Mutel et al. 2018 ;Huijbregts et al. 2016 ; Bulle et al. 2019 ; Verones et al. 2020)
[4] See studies (Moran and Wood 2014; Suh et al. 2004; Suh and Huppes 2005; Islam et al. 2016; Hertwich et al. 2015; Tukker et al. 2018; Lesage and Muller 2017)

1.4.2 Operationalizing regionalized LCA to assess a large portfolio of products

Increasingly, companies are making product footprint and comparative claims available on the individual product level. International food companies often have a global footprint in their product supply chain and have a large-scale complex food product portfolio for the same functionality sold in various consumer markets, with different product recipes, unknown agricultural commodity sourcing and spatial variabilities of agricultural ingredient production.

In this thesis, the comparison of animal-based dairy butter with plant-based spread alternative is used as the demonstration case study to examine the feasibility, potential challenges and validity of operationalizing a regionalized LCA for a large portfolio of products. Previous studies show that the production of plant-based spreads (sold in UK, Germany and France) have lower climate change impacts and less land use compared with dairy butter based on the analysis of a single product for each country (Nilsson et al. 2010; Milà i Canals et al. 2013); however, the validity is yet known for broader products and consumer country markets if climate benefit of plant-based alterative over dairy butter hold regardless of the variabilities of

product recipes and geographies. Considering the climate-water-land nexus (Ringler et al. 2013; Kraucunas et al. 2015; Conway et al. 2015), is there a risk of shifting impacts from climate to water scarcity and land occupation, and what are the key opportunities for impact mitigation? Several further challenges are described below:

- The nature of the large scale of product portfolio and consumer markets to be assessed creates practical challenges for the required effort of pursuing higher regionalization details and data quality of LCA results.
- In this case study, there are 212 different types of plant-based spread product sold on 21 markets. Influenced by consumer preferences, for each consumer country market, there are difference in product characteristics, regarding product recipe design containing different agricultural ingredients and sourcing countries (partially known or unknown by the company), packaging choices, processing, upstream supply chain and downstream product distribution logistics. However, these types of product-specific variabilities have not been comprehensively examined before.
- Poore et al. (2018) shows that the farm stage dominates GHG emissions from food, with most of them involving deforestation. Recent studies (Sandström et al. 2018; Pendrill et al. 2019) find global agricultural commodity trade contributes to land use change (LUC) GHG emission. The previous study (Nilsson et al. 2010) comparing plant-based spreads and butter only considered the GHG emissions from land use change (LUC) for a small selection of ingredients, such as palm oil; the effect of comprehensive inclusion of the LUC induced GHG emissions for broader relevant agricultural commodities are unknown.

1.4.3 Assessing the emerging power to gas technologies

Various national incentive schemes are introduced to financially support clean fuel development in Europe based on sustainability criteria requiring, at minimum, the reduction of carbon footprint (Koponen and Hannula 2017; Meylan et al. 2017; Spielmann et al. 2015; Kreeft 2018), yet the validity of the carbon footprint of PtG is hindered by several pitfalls as reviewed in chapter 4 of the thesis, including the allocation problem related to CO_2 feedstock and regionalized LCA model choices of modeling electricity carbon emission factors under different temporal resolutions, as further elaborated below.

- Several studies show LCA results of PtG production are sensitive to the choice of allocation method on carbon flows (Sternberg and Bardow 2015; Zhang et al. 2017; Parra et al. 2017; Koj et al. 2019). However, inconsistencies are found for different

supporting schemes among EU countries to support the types of CO_2 used for PtG. For example, in the Italian support scheme for biomethane as transportation fuel, synthetic natural gas (SNG) can only use carbon from a biogenic source, whereas in Switzerland, the support for SNG used for vehicles can only consider ambient direct air capture (Kreeft 2018). Hence, the understanding of the influence of CO_2 feedstock choice and accounting is crucial for the carbon footprint of PtG production system.

- The GHG intensity of electricity is found to be the crucial factor for the carbon footprint of PtG (Spielmann et al. 2015; Koj et al. 2019). Yet, the influence of methodological choices (Sotos 2015; Brander et al. 2018; Soimakallio et al. 2011; Qu et al. 2017) for modeling the regionalized grid electricity GHG emissions was given little attention in the LCA of PtG studies as shown in the detailed literature review conducted in Chapter 4. For example, should the electricity emission factors be calculated based on territorial production-based vs consumption-based perspective without differentiating specific users in a region, or it should differentiate different users based on the contractual relationship, such as the guarantees of origins (GOO) (Association of Issuing Bodies 2019)? As the carbon footprint of electricity supply have high temporal variabilities (Vuarnoz and Jusselme 2018; Messagie et al. 2014), would the choice of different temporal resolution (yearly, hourly or seasonal) of electricity GHG emissions have a large influence for calculating the carbon footprint of PtG and what should be proper temporal resolution to consider?

1.5 Objectives, approaches, and content of this thesis

In this thesis, the core research objectives are summarized below. They address regionalized LCA issues on a single agricultural commodity level (Objective 1), on the food product level (Objective 2) and on the technology development level (Objective 3), respectively.

- **Objective 1:** How to improve the process-based regionalized LCA to solve the cross-border commodity flow tracing between industries from different national jurisdictions?
- **Objective 2:** How to operationalize the regionalized LCA approach for assessing the large-scale portfolio of products, such as dietary choice comparison between plant-based fat spreads over dairy butter considering the variabilities of product recipes, geographies, and different environmental problems?

- **Objective 3:** What is the influence in assessing the carbon footprint of power to gas, considering different regionalized LCA model choices for modeling electricity supply under different temporal resolutions and allocation methods of CO_2 feedstock?

The objectives, methods and specific applications developed in this thesis are summarized in Figure 1.4, with the structure of the thesis further elaborated below.

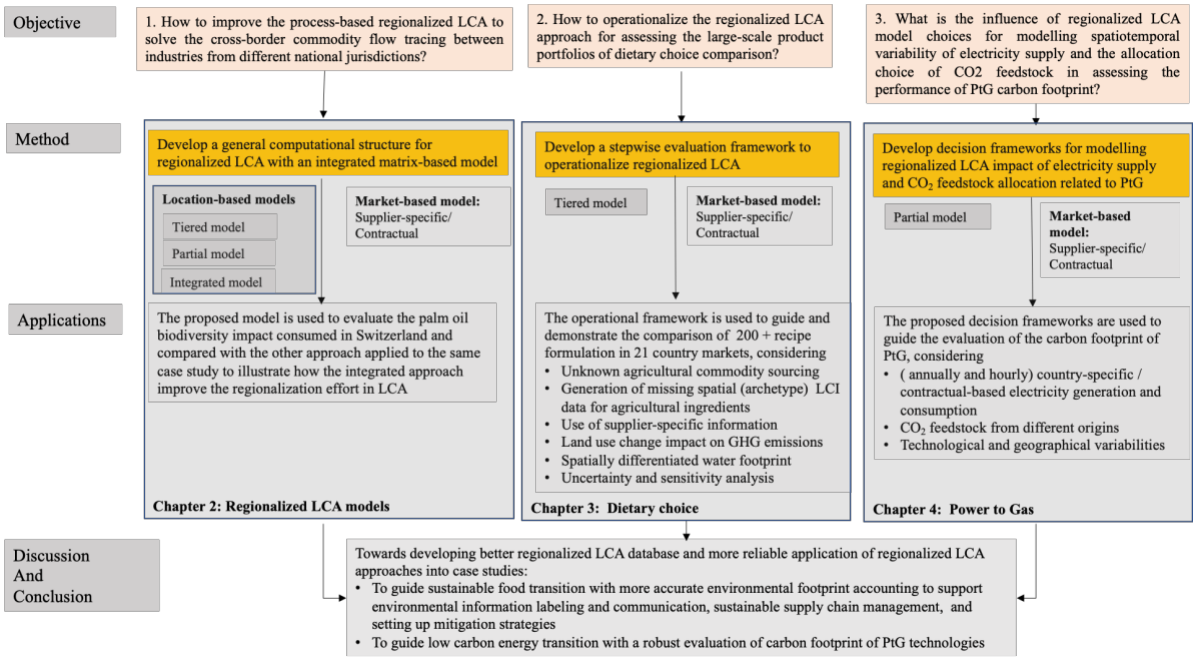

Figure 1.4 Methodological structure of the thesis in relationship of the research objectives

Chapter 2: A general computational structure for process-based regionalized LCA. This chapter answers the first core objective. The key content is described below:

- It starts with a literature review of the definition of regionalized LCA, computation models and approaches of handling product supply chain sourcing information in regionalized LCA and its applications for food and energy; then the definition of key elements of regionalized LCA is given.
- Stemming from the supply and use concept and the ecoinvent model structure, a general matrix-based computational structure is developed for process-based regionalized LCA to improve the inclusion of spatial details of tracing the spatial locations of cross-border product flows along supply chains from production to consumption.
- It is validated with a numerical example and demonstrated with a case study from literature for an improved accuracy of impact results. Further comparison of several predominant assumptions used in process-based regionalized LCAs for deriving spatial location information are examined with numerical examples.

Chapter 3: Operationalizing the regionalized LCA for large-scale food product comparison. This chapter answers the second objective regarding the operationalization of a regionalized LCA approach with a case study aiming to assess and compare two large-scale portfolios of dietary products: plant-based vs diary butter. The key contents are described below.

- It develops a stepwise framework guiding each step how to perform the regionalized LCA analysis with the key focus on how to efficiently manage data quality of regionalized LCA analysis with limited time effort by using contribution analysis to prioritize spatial data development together the uncertainty evaluation of data quality of LCI datasets.
- The product supply chain sourcing country estimation are combined with (existing or newly generated) spatial (archetype) LCI data for key agricultural ingredients and dairy product to perform core regionalization LCA calculation.
- Country-specific GHG emissions due to land use change are included for each relevant vegetable oil ingredient and dairy feed input.
- To assess the data quality and validity of regionalized LCA results, this study illustrates several approaches to assess and visualize uncertainty of results. For parameter uncertainty, the geometric standard deviation (GSD) of all key datasets and parameters are characterized with pedigree scores to perform analytical uncertainty propagation of the regionalized LCA results in a streamlined and efficient way for all scenarios under study. For uncertainties related to natural variability or subjective choices, various sensitivity analyses are performed for different LUC GHG model assumptions and allocation keys of agricultural and animal products. The potential uncertainty introduced by the supply chain sourcing variabilities of agricultural commodities is addressed by conducting the worst supply chain scenario analysis to verify the conclusion of the regionalized LCA estimation based on the tiered supply chain modeling approximation approach. For inter-product variabilities, the impact results of 211 plant-based spreads and 21 dairy butters sold in 21 consumer markets are analyzed and visualized using the non-parametric kernel density estimation (KDE) approach to identify the product-specific variabilities and potential overlap between dairy butter and plant-based alternative.

Chapter 4: **The carbon footprint of Power to gas**. This chapter answers the third core objective with the key contents described below.

- It develops a systematic methodological framework for assessing PtG. The proposed framework is illustrated with three actual PtG demonstration sites in Europe with different technology choices, system configurations, and regional characteristics.
- The investigated regionalized LCA model choices of calculating electricity emission factors are either "location-based approaches" from a territorial production-based vs consumption-based perspective without differentiating specific users in a given region under hourly or yearly temporal resolution, or "market-based approach" differentiating electricity users, for example, based on a contractual relationship, such as the guarantees of origins (GOO).
- Carbon feedstocks under investigation are sourced from different origins (biogenic, fossil, or ambient air) with or without competitive use.

Chapter 5: Key findings and Discussion. The key findings, including scientific and practical relevance of the different methods and applications developed in this thesis are discussed in relation to the objectives of this thesis and the literature. Study limits and further research needs are outlined for using the regionalized LCA in steering the sustainable food and energy transition.

Chapter 6. Conclusion. Conclusions are drawn for the regionalized LCA method development and its practical applications in food and energy product.

Reference

Association of Issuing Bodies (2019) European Residual Mixes Results of the calculation of Residual Mixes for the calendar year 2018

Bengoa X, Chappuis C, Guignard C, et al (2020) World Food LCA Database Documentation. Version 3.5.1, January 2020. Quantis, Lausanne, Switzerland. World Food LCA Database http://www quantis-intl com/wfldb/files/WFLDB_MethodologicalGuidelines_v3 0 pdf

Bjelle EL, Többen J, Stadler K, et al (2020) Adding country resolution to EXIOBASE: impacts on land use embodied in trade. Economic Structures 9:14. https://doi.org/10.1186/s40008-020-0182-y

Blanco H, Codina V, Laurent A, et al (2020) Life cycle assessment integration into energy system models: An application for Power-to-Methane in the EU. Applied Energy 259:114160. https://doi.org/10.1016/j.apenergy.2019.114160

Blanco H, Faaij A (2018) A review at the role of storage in energy systems with a focus on Power to Gas and long-term storage. Renewable and Sustainable Energy Reviews 81:1049–1086. https://doi.org/10.1016/j.rser.2017.07.062

Boulay A-M, Bare J, Benini L, et al (2017) The WULCA consensus characterization model for water scarcity footprints: assessing impacts of water consumption based on available water remaining (AWARE). Int J Life Cycle Assess 1–11. https://doi.org/10.1007/s11367-017-1333-8

Brandão M, Levasseur A, Kirschbaum MUF, et al (2013) Key issues and options in accounting for carbon sequestration and temporary storage in life cycle assessment and carbon footprinting. Int J Life Cycle Assess 18:230–240. https://doi.org/10.1007/s11367-012-0451-6

Brander M, Gillenwater M, Ascui F (2018) Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. Energy Policy 112:29–33. https://doi.org/10.1016/j.enpol.2017.09.051

Brown T, Schlachtberger D, Kies A, et al (2016) Sector-Coupling in a Simplified Model of a Highly Renewable European Energy System. 59

Bulle C, Margni M, Patouillard L, et al (2019) IMPACT World+: a globally regionalized life cycle impact assessment method. Int J Life Cycle Assess 24:1653–1674. https://doi.org/10.1007/s11367-019-01583-0

Buttler A, Spliethoff H (2018) Current status of water electrolysis for energy storage, grid balancing and sector coupling via power-to-gas and power-to-liquids: A review. Renewable and Sustainable Energy Reviews 82:2440–2454. https://doi.org/10.1016/j.rser.2017.09.003

Cardellini G, Valada T, Cornillier C, et al (2018) EFO-LCI: A New Life Cycle Inventory Database of Forestry Operations in Europe. Environ Manage 61:1031–1047. https://doi.org/10.1007/s00267-018-1024-7

Chaudhary A, Pfister S, Hellweg S (2016) Spatially Explicit Analysis of Biodiversity Loss Due to Global Agriculture, Pasture and Forest Land Use from a Producer and Consumer Perspective. Environ Sci Technol 50:3928–3936. https://doi.org/10.1021/acs.est.5b06153

Clarke LE, Jiang K, Akimoto K, et al (2015) Chapter 6 Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press Cambridge GB

Colomb V, Amar SA, BASSET-MENS C, et al (2015) AGRIBALYSE, the French LCI database for agricultural products: high quality data for producers and environmental labelling. OCL Oilseeds and fats crops and lipids 22:D104. https://doi.org/10.1051/ocl/20140047

Durlinger B, Tyszler M, Scholten J, et al (2014) Agri-Footprint; a Life Cycle Inventory database covering food and feed production and processing. In: Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector. pp 310–317

ecoinvent (2018) ecoinvent Version 3. https://www.ecoinvent.org/database/database.html. Accessed 1 Nov 2018

Faria PCS, Labutong N (2019) A description of four science-based corporate GHG target-setting methods. Sustainability Accounting, Management and Policy Journal 11:591–612. https://doi.org/10.1108/SAMPJ-03-2017-0031

Field CB, Barros VR, Mastrandrea MD, et al (2014) Summary for policymakers. In: Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp 1–32

Flagg JA (2015) Aiming for zero: what makes nations adopt carbon neutral pledges? Environmental Sociology 1:202–212. https://doi.org/10.1080/23251042.2015.1041213

Friis C, Nielsen JØ (2019) Telecoupling: Exploring Land-Use Change in a Globalised World. Springer

Gills B, Morgan J (2020) Global Climate Emergency: after COP24, climate science, urgency, and the threat to humanity. Taylor & Francis

Hellweg S, Canals LM i (2014) Emerging approaches, challenges and opportunities in life cycle assessment. Science 344:1109–1113. https://doi.org/10.1126/science.1248361

Hoekstra AY, Wiedmann TO (2014) Humanity's unsustainable environmental footprint. Science 344:1114–1117. https://doi.org/10.1126/science.1248365

Huijbregts MAJ, Steinmann ZJN, Elshout PMF, et al (2016) ReCiPe 2016: a harmonized life cycle impact assessment method at midpoint and endpoint level report I: characterization

IPCC (2014) Summary for Policymakers. AR5. In: IPCC 5th Assessment Synthesis Report. http://ar5-syr.ipcc.ch/topic_summary.php. Accessed 25 Oct 2020

Jacobson MZ, Delucchi MA (2011) Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials. Energy Policy 39:1154–1169. https://doi.org/10.1016/j.enpol.2010.11.040

Kastner T, Kastner M, Nonhebel S (2011) Tracing distant environmental impacts of agricultural products from a consumer perspective. Ecological Economics 70:1032–1040. https://doi.org/10.1016/j.ecolecon.2011.01.012

Koj JC, Wulf C, Zapp P (2019) Environmental impacts of power-to-X systems - A review of technological and methodological choices in Life Cycle Assessments. Renewable and Sustainable Energy Reviews 112:865–879. https://doi.org/10.1016/j.rser.2019.06.029

Koponen K, Hannula I (2017) GHG emission balances and prospects of hydrogen enhanced synthetic biofuels from solid biomass in the European context. Applied Energy 200:106–118. https://doi.org/10.1016/j.apenergy.2017.05.014

Kreeft G (2018) Legislative and Regulatory Framework for Power-to-Gas in Germany, Italy and Switzerland. STORE&GO Project

Lambin EF, Meyfroidt P (2011) Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences 108:3465–3472

Lenzen M, Pade L-L, Munksgaard J (2004) CO2 Multipliers in Multi-region Input-Output Models. Economic Systems Research 16:391–412. https://doi.org/10.1080/0953531042000304272

Levasseur A, Lesage P, Margni M, et al (2010) Considering time in LCA: dynamic LCA and its application to global warming impact assessments. Environmental science & technology 44:3169–3174

Luo X, Wang J, Dooner M, Clarke J (2015) Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy 137:511–536. https://doi.org/10.1016/j.apenergy.2014.09.081

Mekonnen MM, Hoekstra AY (2016) Four billion people facing severe water scarcity. Science Advances 2:e1500323. https://doi.org/10.1126/sciadv.1500323

Merciai S, Schmidt J (2018) Methodology for the Construction of Global Multi-Regional Hybrid Supply and Use Tables for the EXIOBASE v3 Database. Journal of Industrial Ecology 22:516–531. https://doi.org/10.1111/jiec.12713

Messagie M, Mertens J, Oliveira L, et al (2014) The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment. Applied Energy 134:469–476. https://doi.org/10.1016/j.apenergy.2014.08.071

Meyfroidt P, Lambin EF, Erb K-H, Hertel TW (2013) Globalization of land use: distant drivers of land change and geographic displacement of land use. Current Opinion in Environmental Sustainability 5:438–444. https://doi.org/10.1016/j.cosust.2013.04.003

Meylan FD, Piguet F-P, Erkman S (2017) Power-to-gas through CO2 methanation: Assessment of the carbon balance regarding EU directives. Journal of Energy Storage 11:16–24. https://doi.org/10.1016/j.est.2016.12.005

Michalski J, Bünger U, Crotogino F, et al (2017) Hydrogen generation by electrolysis and storage in salt caverns: Potentials, economics and systems aspects with regard to the German energy transition. International Journal of Hydrogen Energy 42:13427–13443. https://doi.org/10.1016/j.ijhydene.2017.02.102

Moore J, Shabani B (2016) A Critical Study of Stationary Energy Storage Policies in Australia in an International Context: The Role of Hydrogen and Battery Technologies. Energies 9:674. https://doi.org/10.3390/en9090674

Moran D, Wood R (2014) Convergence Between the Eora, Wiod, Exiobase, and Openeu's Consumption-Based Carbon Accounts. Economic Systems Research 26:245–261. https://doi.org/10.1080/09535314.2014.935298

Mutel C, Liao X, Patouillard L, et al (2018) Overview and recommendations for regionalized life cycle impact assessment. Int J Life Cycle Assess. https://doi.org/10.1007/s11367-018-1539-4

Parra D, Zhang X, Bauer C, Patel MK (2017) An integrated techno-economic and life cycle environmental assessment of power-to-gas systems. Applied Energy 193:440–454. https://doi.org/10.1016/j.apenergy.2017.02.063

Peano L, Bengoa X, Humbert S, et al (2012) The World Food LCA Database project: towards more accurate food datasets. In: Proceedings 2nd LCA conference

Pfister S, Bayer P (2014) Monthly water stress: spatially and temporally explicit consumptive water footprint of global crop production. Journal of Cleaner Production 73:52–62. https://doi.org/10.1016/j.jclepro.2013.11.031

Pfister S, Vionnet S, Levova T, Humbert S (2016) Ecoinvent 3: assessing water use in LCA and facilitating water footprinting. Int J Life Cycle Assess 21:1349–1360. https://doi.org/10.1007/s11367-015-0937-0

Poore J, Nemecek T (2018a) Reducing food's environmental impacts through producers and consumers. Science 360:987–992. https://doi.org/10.1126/science.aaq0216

Qu S, Liang S, Xu M (2017) CO2 Emissions Embodied in Interprovincial Electricity Transmissions in China. Environ Sci Technol. https://doi.org/10.1021/acs.est.7b01814

Quantis (2018) Measuring Fashion environmental impact report. In: Quantis. https://quantis-intl.com/measuring-fashion-report-2018/. Accessed 1 Nov 2018

Rebitzer G, Ekvall T, Frischknecht R, et al (2004) Life cycle assessment: Part 1: Framework, goal and scope definition, inventory analysis, and applications. Environment International 30:701–720. https://doi.org/10.1016/j.envint.2003.11.005

Ripple W, Wolf C, Newsome T, et al (2019) World scientists' warning of a climate emergency. BioScience

Ritchie H, Roser M (2013) Land use. Our World in Data

Ritchie H, Roser M (2017a) CO_2 and greenhouse gas emissions. Our world in data

Ritchie H, Roser M (2017b) Water use and stress. Our World in Data

Ritchie H, Roser M (2020) Environmental impacts of food production. Our world in data

Robinius M, Otto A, Syranidis K, et al (2017) Linking the Power and Transport Sectors—Part 2: Modeling a Sector Coupling Scenario for Germany. Energies 10:957. https://doi.org/10.3390/en10070957

Rogelj J, Shindell D, Jiang K, et al (2018) Mitigation pathways compatible with 1.5 C in the context of sustainable development. In: Global warming of 1.5° C. Intergovernmental Panel on Climate Change (IPCC), pp 93–174

Schutter OD (2011) How not to think of land-grabbing: three critiques of large-scale investments in farmland. The Journal of Peasant Studies 38:249–279. https://doi.org/10.1080/03066150.2011.559008

Soimakallio S, Kiviluoma J, Saikku L (2011) The complexity and challenges of determining GHG (greenhouse gas) emissions from grid electricity consumption and conservation in LCA (life cycle assessment) – A methodological review. Energy 36:6705–6713. https://doi.org/10.1016/j.energy.2011.10.028

Sotos M (2015) GHG protocol scope 2 guidance. An amendment to the GHG Protocol Corporate Standard

Spielmann M, Ruiz S, Zah R (2015) Analyse der Umwelt-Hotspots von Strombasierten Treibstoffen. Quantis Schweiz/Deutschland, Zurich

Stadler K, Wood R, Bulavskaya T, et al (2018) EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. Journal of Industrial Ecology 22:502–515. https://doi.org/10.1111/jiec.12715

Sternberg A, Bardow A (2015) Power-to-What? – Environmental assessment of energy storage systems. Energy Environ Sci 8:389–400. https://doi.org/10.1039/C4EE03051F

Verones F, Hellweg S, Antón A, et al (2020) LC-IMPACT: A regionalized life cycle damage assessment method. Journal of Industrial Ecology n/a: https://doi.org/10.1111/jiec.13018

Verones F, Pfister S, Zelm R van, Hellweg S (2017) Biodiversity impacts from water consumption on a global scale for use in life cycle assessment. Int J Life Cycle Assess 22:1247–1256. https://doi.org/10.1007/s11367-016-1236-0

Vionnet S, Lessard L, Offutt A, et al (2012) Quantis water database–technical report. Quantis International Lausanne, Switzerland Available via Quantis International: http://www quantis-intl com/waterdatabase php Accessed 2:

Vuarnoz D, Jusselme T (2018) Temporal variations in the primary energy use and greenhouse gas emissions of electricity provided by the Swiss grid. Energy 161:573–582. https://doi.org/10.1016/j.energy.2018.07.087

Walenta J (2020) Climate risk assessments and science-based targets: A review of emerging private sector climate action tools. WIREs Climate Change 11:e628. https://doi.org/10.1002/wcc.628

Willett W, Rockström J, Loken B, et al (2019) Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. The Lancet. https://doi.org/10.1016/S0140-6736(18)31788-4

Wood R, Stadler K, Bulavskaya T, et al (2015) Global sustainability accounting-developing EXIOBASE for multi-regional footprint analysis. Sustainability (Switzerland) 7:138–163. https://doi.org/10.3390/su7010138

Wood R, Stadler K, Bulavskaya T, et al (2014) Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability 7:138–163. https://doi.org/10.3390/su7010138

Yang Y (2016) Toward a more accurate regionalized life cycle inventory. Journal of Cleaner Production 112:308–315. https://doi.org/10.1016/j.jclepro.2015.08.091

Zeman FS, Keith DW (2008) Carbon neutral hydrocarbons. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 366:3901–3918. https://doi.org/10.1098/rsta.2008.0143

Zhang X, Bauer C, Mutel CL, Volkart K (2017) Life Cycle Assessment of Power-to-Gas: Approaches, system variations and their environmental implications. Applied Energy 190:326–338. https://doi.org/10.1016/j.apenergy.2016.12.098

Zhang X, Witte J, Schildhauer T, Bauer C (2020) Life cycle assessment of power-to-gas with biogas as the carbon source. Sustainable Energy Fuels 4:1427–1436. https://doi.org/10.1039/C9SE00986H

2 A general computational structure for process-based regionalized LCA

Regionalized LCA increases the accuracy by considering site-specific production conditions and characterization factors. However, there remain challenges for better tracing supply chains and acquiring spatial locations of a product from origins of production to locations of consumption to be incorporated into the process-based regionalized LCA framework. Stemming from the supply and use concept and network modeling, a general matrix-based computational structure is developed for process-based regionalized LCA to improve the inclusion of spatial details of tracing the spatial locations of cross-border product flows from production to consumption. It is validated with a numerical example and demonstrated with a case study from literature for an improved accuracy of impact results. Further comparison of several predominant assumptions used in process-based regionalized LCAs for deriving spatial location information are examined with numerical examples. Results show large variabilities of impact results and indicate the potential over- or under-estimation of impact results with the assumptions of the global production share, global export share, direct trade adjustment, and net import data. The develop model in this chapter can be used to reduce the uncertainties associated with supply chain sourcing estimation introduced by arbitrary assumptions. It also offers a coherent and transparent way of analyzing the influence from different trade assumptions or incomplete inclusion of trade data and supply chain activities in a process-based regionalized LCA analysis.

This chapter is based on the submitted manuscript *X. Liao, M. Margni, F. Maréchal. A general computational structure for regionalized LCA* and the extension of Liao X; 2017; Incorporating FAO trade and production database to estimate supply chain location information for agricultural products; 67th Swiss LCA Discussion Forum, Zurich, Switzerland.

2.1 Introduction

Life cycle assessment (LCA) has been routinely applied into various fields, such as product and organization environmental footprint (Finkbeiner 2014; Martínez-Blanco et al. 2015; Lehmann et al. 2016; Manfredi et al. 2015; European Commission 2018), environmental product declarations, communication and labeling (Minkov et al. 2015; Schmidt 2009; Fet et al. 2009; ISO 14025 2006; Borghi 2013), corporate Carbon disclosure project (CDP), research and technology innovation (Tufvesson et al. 2013), as well as legislation and policy decision-making process (Reale et al. 2017). Traditional LCIA methods or LCI often assume a static and site-generic (continental or global) scale, assuming the homogeneity of the impact of elementary flows and assuming the same coefficient for technosphere and biosphere for product across different locations. However, these assumptions do not often hold, especially for agricultural commodities (Poore and Nemecek 2018) and electricity production (Mutel et al. 2012; Qu et al. 2017, 2018). With increasing demand and rising importance for LCA, in the past decades, progress has been made in the LCA community to increase the reliability of LCA with the development of regionalization of LCA that overcome the assumption of homogeneity across locations (Hellweg and Milà i Canals 2014).

Various studies give the definition of the regionalized LCA. Depending on how detailed the spatial differentiation has been made, (Potting and Hauschild 1997, 2006) introduced the different definition related to spatial differentiations in life cycle impact assessment, including site-generic (continental or global level), site-dependent(some spatial differentiation, for example, the country or watershed level), and site-specific (a very detailed spatial differentiation by considering sources at specific locations, for example, the hyper GIS level). Mutel (2009) argues that regionalized LCA applies the site-dependent impact assessment factors to the environment intervention matrix, before calculating the aggregated results with matrix inversion. Hellweg and Milà i Canals (2014) argues the regionalized LCA increase the accuracy by considering site-specific production conditions […] and the sensitivity of ecosystems. Reinhard et al. (2017) refers it to *site-specific* generation and assessment of cradle to gate unit process raw (UPR) datasets for regionalized LCI. Yang (2016) defines "Regionalized LCI […] as the study of the location and quantity of environmental emissions that occur throughout the life cycle of a product within the geographic boundary studied, or the study of the geographic distribution of a product's life cycle emissions"; Yang et al. (2017) further considers the regionalized LCA consists of "*region-specific* UPRs, regional process

output volumes, interregional commodity flow and *region-specific* CFs". Patouillard et al. (2018) differentiates the terms between regionalization and spatialization, referring regionalization in LCA as "a term to describe the representativeness of the processes and phenomena of a given region" and spatialization as the "Act of assigning a location to something, e.g., a flow". The meaning of regionalized LCA is perceived differently with different scopes of coverage and level of details, and there is no universally accepted meaning or definition when it comes to the regionalized LCA.

Furthermore, several studies (Kastner et al. 2011; Qu et al. 2017 a, b;Yang and Heijungs 2017) illustrate that the regional LCA impact results are potentially sensitive to trade assumptions, yet there remain challenges for better tracing supply chains (O'Rourke, 2018) and acquiring spatial locations (Hellweg and Milà i Canals 2014) of a product from origins of production to locations of consumption for the process-based life cycle assessment. In practice, increasingly, there are more attempts to include cross-border trade and spatial location data for some product, such as grid electricity mix (ecoinvent 2018), however, this is not made available for many products, often due to lack of spatial data. Bilateral trade data, production and consumption data among countries are increasing used for LCA studies, such as the FAOSTAT for agricultural commodities; however, the FAO data only reports the last country from which the food item is traded but not the actual country where the item was produced, as pointed out by Chaudhary et al. (2016). Countries are simultaneous importing and exporting of identical or similar product, known as cross-hauling or two-away bilateral trade (Court and Jackson 2015). Some countries reported in the trade data are only virtual trading hubs, without the actual production activities by re-importing and re-exporting. Thus, the exact sourcing countries are unknown just based on the apparent trade statistics from FAOSTAT. With these limitations, the incorporation of such data into process-based regionalized LCA is often made arbitrarily. For example, average market mixes (global production or export share) are often used as an approximation for consumption mix (Hellweg and Milà i Canals 2014; Nemecek et al. 2015; Bengoa et al. 2020), which ignores different country-specific trade pattern. When assessing the biodiversity impact of palm oil consumed in Switzerland, Chaudhary et al. (2016) considered the trade data from FAOSTAT to derive the sourcing location of purchased palm oil, but assuming the country of import is the same as country of production origins unless the importing countries do not have local production, where a further approximation is made based on the proportion of global export share from the biggest producers of a product. Several studies (Kastner et al. 2011; Li et al. 2013; Qu et al. 2017a,b; Tranberg et al. 2019) proposed

more mature approaches for tracing the product flows from country of production to country of consumptions with applications into the electricity and agricultural products, however, they only narrowly focus on a single product flow with the focus of single commodity flow tracing in a global supply chain, and none of them are formulated in the framework of life cycle assessment. While the "top-down" multi-regional input out (MRIO) approaches have been developed to address the complexity of supply chain involving trade activities (Tukker et al. 2006; Wiedmann 2009; Moran and Wood 2014a; Wood et al. 2015a, b; Stadler et al. 2018; Merciai and Schmidt 2018; Bjelle et al. 2020), they are made on a sector scale, suffering the problem of aggregation with low product specificity which is required by the bottom-up process-based LCA. The grouping of multiple product into a single category might lead to under/over estimation of their impacts (Chaudhary et al. 2016).

With the pitfalls mentioned above, this study aims to provide a generic matrix-based computational structure for process-based regionalized LCA to improve the inclusion of spatial details of tracing the spatial locations and impacts of cross-border product flows from origin of production to destination of consumption. It starts with the site-generic LCA model and its limitations (section 2.2), followed with providing a set of definitions of regionalized LCA terms used for this study (section 2.3) and a literature review of regionalized LCA (section 2.4) focusing mainly on the computation models. The general regionalized LCA computational models are then described in section 2.5, with the model validation, comparison and demonstration adapted from a literature case study given in section 2.6. The conclusion is drawn in section 2.7.

2.2 The computational structure of site-generic LCA and its limitations

The standard matrix formulation for calculating a product life cycle impact assessment given is shown in (2.1) by (Heijungs 1994; Heijungs and Suh 2013; Suh 2004), hereafter the Heijungs-Suh (HS) model. C the characterization factor matrix, B the intervention matrix, A the technology coefficient matrix, f is the final demand. See the detailed illustration and descriptions in Appendix 1 followed by this chapter.

$$H = CBA^{-1}\mathrm{f} \tag{2.1}$$

Whereas, following the supply-use framework (Suh et al.2010), the life cycle impact results, denoted by H, can be computed by using (2.2). See the detailed illustration and descriptions in Appendix 2.

$$H = CB\,(V' - U)^{-1} f = C\tilde{B}(I - A)^{-1} f \quad (2.2)$$

The term $(\mathbf{I} - \mathbf{A})^{-1}$ is called Leontief inverse multiplier in the input-output economics. All flows are measured with physical units. V' denotes the supply or make matrix, U the use matrix and f the final demand and $\tilde{\boldsymbol{B}} = \mathbf{B}\ \mathbf{x}^{\wedge -1}$, x denotes the total supply or output (V). Mathematically, these two models are interchangeable by using (2.3):

$$A = V' - U \quad (2.3)$$

The supply-use model is recommended to be used for process-based LCA, rather than the HS model (Heijungs 1994; Heijungs and Suh 2013; Suh 2004) for several reasons: firstly, it has a clear economic meaning from the input-out economics rather than an arbitrary definition of "negative and positive" sign from the HS model; secondly, it has potentially more complete system boundaries, for example when all trading partners of a product are included, therefore reducing the truncation errors from incomplete coverage of economic activities (Lenzen 2000; Pomponi and Lenzen 2018). The standard models (2.1)(2.2) are generally valid when the following conditions are met: (i) the technological coefficients and environmental emissions are homogenous for providing the same function across different locations. (ii) the impact of emitting the same pollutants or extracting the same resource is homogenous across locations.

However, the first condition can hardly meet when it comes to electricity (Mutel et al. 2012; Qu et al. 2017a,b, 2018) and agri-food commodities (Poore and Nemecek 2018), as the production technologies and environmental emissions often vary depending on regional practice and resource endowment at different geographical locations. For the second condition, (Mutel et al. 2019) reviewed the existing life cycle impact methods and show many impact categories are sensitive to the locations of environmental elementary flows. For example, the water scarcity is highly variable depending on the locations of withdrawal or release (Boulay et al. 2017) and the biodiversity impact of land use also vary across space (Chaudhary et al. 2016).

Furthermore, the tele-coupling, referring to the socioeconomic and environmental interactions between distant coupled human and natural system, has become more extensive and intensive in the globalized era (Hull and Liu 2018). With the involvement of spatial heterogeneity, the understanding of spatial connection or tele-coupling of activities through trade of product becomes vitally important for modeling regionalized impact of purchased product originally produced from other locations. The LCA analysis become even more complicated with cross-

border trade activities. For trade relationship, it can be broadly classified into three scenarios following Lenzen et al. (2004) as illustrated in Figure 2.1 a) autonomous economy: there is no foreign trade, product technology is homogenous in that region; b) Uni-directional trade: there is trade across regions, but it is uni-directional from one region to another; c) network trade: the trade is multi-directional in a global value chain. Each country is simultaneously trading with the rest of world for various products. Some of countries are just trading hubs without domestic production, only importing and exporting product. The real-world situation is closer to the scenario c).

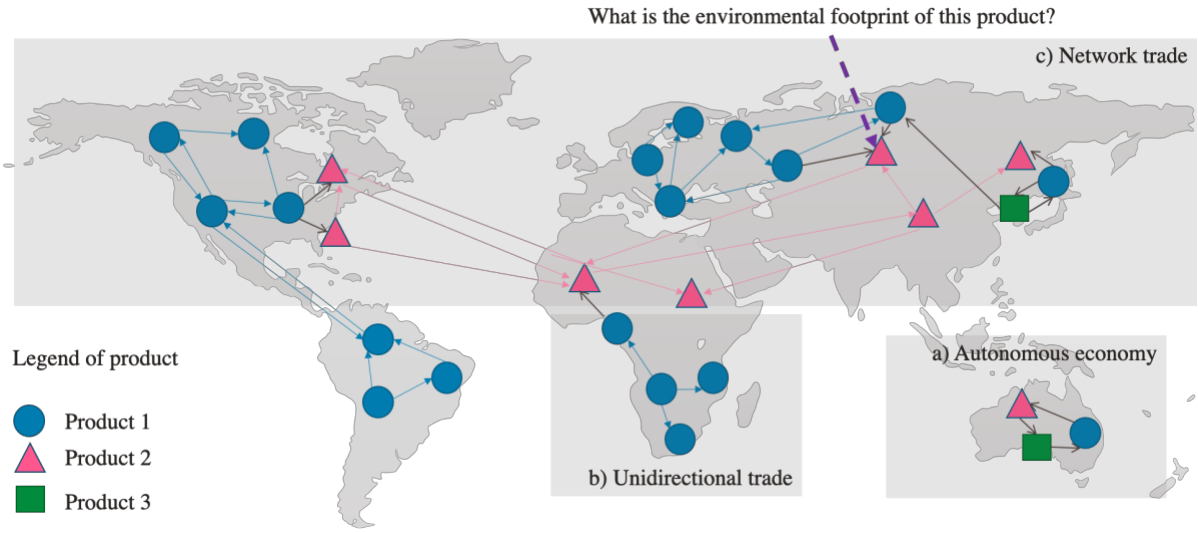

Figure 2.1 The complexity of global value chain of three products

Thus, ideally if a consumer purchases a product in the shape of "red diamond" product 2 in the Eastern Europe as shown in Figure 2.1 and want to understand its environmental impact, we should consider the following: i) the inter-commodity relationship of different product; ii) mapping the product flow from production origin to location of consumption; iii) spatially explicit life cycle inventory analysis of producing a product in a location and sensitivity of elementary flows to local environment and population (spatially explicit characterization factors). These attributes lead to the definition of the regionalized LCA, as further elaborated in the following section.

2.3 Regionalized LCA: a recommended definition

Given the lack of harmonized definition for regionalized LCA (Potting and Hauschild 1997, 2006; Mutel et al.,2009; Hellweg and Milà i Canals 2014; Reinhard et al. 2017; Yang 2016;

Yang et al. 2017; Patouillard et al. 2018), I attempt to provide a set of definitions for key terms relevant for the regionalized LCA in this study:

- *Regionalized unit process raw (UPR) data:* regional differentiation of unit process raw data for both environmental flows (matrices ***B*** *from the HS model with spatial differentiations*) and economic flows (matrices ***A*** *with spatial differentiation*). This definition encompasses both inventory spatialization (attributing a geographic location to an elementary flow) and inventory regionalization (the geographic representativeness of inventory data) from Patouillard et al. (2018). In regional LCA, another important dimension is to separate the local inputs and inputs purchased from other regions. Thus, the consideration of the regional analysis of inter-regional commodity flow is embedded from the very basic component of a regionalized UPR.
- *Regionalized elementary flow:* the elementary flow (matrices ***B*** *with spatial differentiations*) in a UPR is regionalized based on either site-dependent (some spatial differentiation, for example, the country or watershed level), site-specific (a very detailed spatial differentiation by considering sources at specific locations, for example, the hyper GIS level) or regionalized archetype. This is equivalent to the inventory spatialization (attributing a geographic location to an elementary flow) from Patouillard et al. (2018).
- *Regionalized archetypes:* the combination of archetypes, such as population density classes, with spatial information, such as a city name and location. The definition is from Mutel et al. (2019).
- *Regionalized characterization factors (CFs):* characterizing spatiotemporal variabilities of regionalized elementary flows (matrices ***C*** *with spatial differentiations*). This is equivalent to the "Impact regionalization" from Patouillard et al. (2018).
- *Regionalized product and trade flow data:* describing the total supply, production and consumption of a product for a given geographical region, as well as the directional trade data (import and export) of products among regions. This matrix is important to model inter-regional commodity or product flow to regionalize a site-generic UPR with spatial differentiations into regionalized UPR.
- *Regionalized life cycle inventory:* solving the inventory analysis of the regionalized UPR data to obtain matrices ***G*** *(or* $BA^{-1}\hat{f}$*) with spatial differentiations, consisting of* aggregated system life cycle inventories of spatially differentiated elementary flows.

- *Regionalized life cycle impact assessment:* solving the regionalized life cycle inventory analysis and applying the regionalized characterization factors of elementary flows*, to obtain* the life cycle impact results (matrices ***H*** *with spatial differentiations*), consisting of spatially differentiated regionalized impact results.

In this study, I recommend a full regionalized LCA analysis, at minimum, to include the following main elements: (i) Regionalized unit process raw (UPR), (ii) Regionalized CFs, (iii) the cross-border commodity flow tracing of mapping the product origin of production to destination of consumption for a targeted product (iv) regionalized LCA models for solving the regionalized LCI analysis and applying the regionalized CFs of elementary flows. Further considerations should consider the compatibility with existing process-based LCA database, for example differentiating product from domestic production and market mix in ecoinvent (2018), and address the consistency of matching regionalized CFs and elementary flows regarding nomenclature, spatial scale and data format. Furthermore, as LCA analysis are always defined for a given chosen time, regionalized inventory and impact assessment is always subject to the choice of temporal scale (from hourly to multiple yearly period). The following section will discuss how these main elements are addressed in the existing literature of regionalized LCA and beyond.

2.4 Literature review of the mathematical models used in the regionalized LCA

With the limitation of the site-generic LCA models highlighted in sections (2.1) (2.2), in this section, I focus on the review of the computational models for regionalized LCA, with the focus on how commodity flow tracing and trade assumptions are made in regionalized LCA models. Table 2.1 reviews the recent studies in relation to the main elements listed in section 2.3. The mathematical formulations of most relevant studies are listed Table 2.2. It shows different models have divergent but complementary research focuses. Mutel et al. (2009, 2012) focus on the attributing a geographic location to an elementary flow and the corresponding matching with regionalized CFs, as well as the optimal scale between LCI and CFs. Reinhard et al. (2017) studies the auto-generation of spatial UPR with the incorporation of GIS. Yang et al. (2016, 2017) introduces how the MRIO framework can potentially be leveraged for process-based LCA studies conceptually. When looking outside of the domain of process-based LCA, various EE-MRIO models (Lenzen et al. 2004; Miller and Blair 2009; Wiedmann 2009) study the general approach for how to build multi-regional input-output database, mainly for economic input-out database on a sector level. Kastner et al. (2011) and Qu et al. (2017 a,b)

derived independently how to trace the location and impact of product flow with bilateral trade, production and consumption data from either the quasi-Leontief "demand" or the Ghosh "supply" perspective.

The strengths and weakness of the selected models and condition of their applicability are further elaborated below, specifically focusing on three extreme cases:

- Reinhard et al. (2017) proposed the GIS-based autogenerating of spatial life cycle inventories. It provides a powerful approach for modeling site-specific spatial impact. This type of hyper-regionalization model works well if the location information of activities is perfectly known. This happens when a buyers or company knows exactly where their suppliers are located, and the regionalized impact category is dominated by the direct emissions or resource use. This model can also be used to improve the data quality of LCI dataset on a UPR level by providing higher spatial resolution, although the uncertainties of data associated with scale-down should also be carefully considered.
- Kastner et al. (2011) and Qu et al. (2017a,b)'s models are powerful for tracing product flow from one location to another. It is most relevant when the regionalized impact of product is dominated by region-specific direct impact from the biosphere matrix $\boldsymbol{B}$, such as direct water use, land use or fossil fuel combustion GHG emissions for producing a product when the locations of occurring activities are not known. These models (Kastner, 2011; Qu et al. 2017a,b) can help identify the locations of where the activity occurs and further combine location data with region-specific direct impact. But this type of models only focuses on a single product flow and also do not include the indirect emissions contributed by the inputs of required economic flows in the process-based LCA product system, for example the fertilizer input for agricultural product or fuel production associated with fossil fuel combustion.
- Yang and Heijungs (2017) proposed that ideally the process-based regionalized LCA model should follow the Isard's IRIO (inter-regional input-output) structure, however this is seldomly conducted even for the economic input out-put analysis due to the limited data availability and data collection effort, as it requires very detailed data describing interregional trade flows by region of origin and region of destination, also differentiated by specific industries. In practice, a Chenery-Moses' MRIO (multi-regional input output) structure is used, where interregional trade flows are only specified by region of origin and region of destination, ignoring specific industries. Still, even applying a MRIO-like

process-based regionalized LCA proposed here is still challenging, as it would require the sourcing information for all products consumed in a region is already known and require the sourcing origin information of a product to be specified in the functional unit. These limitations reduced its applicability in the real-world cases.

As discussed above, different models have their strengths and suitable applications, however, none of the models have a dedicated focus on the practical inclusion of spatial details of tracing the spatial locations of cross-border product flows from production to consumption into a process-based regionalized LCA, when the exact product sourcing location data is unknown. The section 2.5 will develop models to overcome the challenge of integrating commodity flow tracing modeling in a regionalized LCA framework.

Table 2.1 Overview of the regionalized LCA components, modeling approach and applications

	Mutel and Hellweg (2009)	**Mutel et al. (2012)**	**EE-MRIO***	**Kastner (2011)**	**Qu (2017)**	**Reinhard et al. (2017)**	**Yang (2016)**	**Yang and Heijungs (2017)**
Applications	Electricity	electricity	Generic	Agriculture	Electricity	Agriculture	Corn	Generic
1. Life cycle inventory								
1.1 Elementary flow	x		x	x	x	x	x	x
1.2 Economic flow	x		x			x	x	x
1.3 Product-specific &high level of details	x	x		x	x	x	x	x
2. LCIA characterization model								
2.1 Elementary flow	x		x			x	x	x
3. Connection of LCI and LCIA								
3.1 scale harmonization		x						
3.2 nomenclature harmonization								
4. Multi-regional trade model				x	x			
4.1 Direct adjustment proximation								
4.2 National or global average proximation								
4.3 Tiered proximation[5]								
4.4 Network modeling				x	x			
4.5 Complete /global supply chain coverage			x		x		x	x

*see more from these studies (Lenzen et al. 2004; Miller and Blair 2009; Wiedmann 2009)

Table 2.2 Comparison of mathematical models used in regionalized LCA studies

Reference	Generic equation, Description and Key contribution
Mutel and Hellweg (2009)	$[G \circ B]\mathrm{diag}(A^{-1}f)$ Each column in G, which corresponds with a technological process in A, has the appropriate weighting values for all environmental interventions at that process's location. As there are normally more processes than geographic locations, there will be many duplicate columns in G. During this matching process, manual intervention may be required if there is no exact match for the geographical locations of processes and characterization factors.
Mutel et al. (2012)	$(MGR) \circ [B(I-A)\ \mathrm{diag}(f)]$ A regionalized LCA does not change the technosphere or biosphere matrices, but several additional matrices are needed to describe the spatial relationships between inventory and impact assessment. We can encapsulate location-specific information by defining two new matrices, M and G. The mapping matrix, M, has rows of technological processes, and columns of inventory spatial units. The geographic transform matrix, G, describes the change of spatial support between the impact assessment method and the inventory database and is composed of the matrix elements. G has rows of inventory spatial units and columns of IASUs. Each row in G should be normalized to sum to one, as row values represent the proportional area of an inventory spatial unit that is located in each IASU.
Mutel et al. (2013)	$CF \cdot B \cdot (I-A)$. A new two-step approach to sensitivity analysis based on contribution to variance (CTV) has been proposed as a global sensitivity test for life cycle assessment.
Yang (2016)	$Bdiag(A^{-1}k)R^T$ R is the regional output percentages (ROP) matrix in which a column represents a process and a row a region, and elements of a column vector denote the proportion of the total output of a process that is produced in different regions. k is a column vector that denotes final demand related to the functional unit defined in a study.
Yang and Heijungs (2017)	$Q_r B_r A_r^{-1} f_r$ Adopting the IRIO model. Process-based MRIO model is also introduced
Lenzen et al. (2004); Miller and Blair (2009); Wiedmann (2009)	$(I-A^*)^{-1}y^*$ EE-MRIO models. Disaggregate the basic model of Leontief into multi-regional input output model. Mainly applied for economic IO database like Exiobase, WIOD, eora, and so forth.
Qu et al. (2017b)	$e^* = e^p(I-\hat{x}^{-1}T)^{-1}$ Flow tracing model based on the supply-driven Ghosh model for electricity modeling, where e^p is grid direct emission; x: total flow; T: trade flow. e^* *is total impact*
Kastner et al. (2011)	$R = (I-A)\hat{p}$ Flow tracing model based on the demand driven quasi-Leontief mode for agricultural product modeling. In the matrix R, where each element r_{ij} is the part of the DMI (direct material input), x_i of country i that is produced in country j.

2.5 Regionalized LCA: computational models

As discussed in section 2.4, the existing models suffer from two drawbacks: (i) the omission of indirect impact from the technology inputs, as in the case of the methods (Kastner, 2011; Qu et al. 2017b); (ii) the lack of product flow tracing model on the product level, as in the following models (Mutel and Hellweg 2009; Reinhard et al. 2017; Yang and Heijungs 2017). The combination of commodity flow tracing model and process-based LCA framework is what is needed. In section 2.5.1, I show how existing regionalized LCA models or data (Mutel and Hellweg 2009; Reinhard et al. 2017) can be combined with commodity flow-tracing models in a special case. In section 2.5.2, I demonstrate a general case for the computational structure of process-based regionalized LCA.

2.5.1 Partial model: combining the flow tracing model and LCA models

As illustrated in Figure 1.3, in some cases, product 1 use product 2 as input, and meanwhile, product 2 also requires product 1 as input. This is called "feedback" loop situation. In this case, the impact of product 1 or product 2 cannot be independently calculated, as they rely on each other as input. Assume there is no such feedback loop between the studied product system and

its technology input, for example the seed cotton farming (the focal product system) use diesel as input for tillage machine, but the diesel production might not require seed cotton as the main technology input. In this case, the regionalized LCA modeling can be improved by combining the flow tracing model introduced by Kastner et al. (2011) and Qu et al.(2017b) with the LCA model provided by Reinhard et al. (2017) that generates region-specific life cycle inventories and by Mutel et al. (2009, 2012) that produces impact results by multiplying elementary flows with region-specific characterization factors. The former model gives the location of activities from production to consumption, and the latter provides the spatially differentiated inventory or impact results for a given location.

Let z_{ij} represents the amount of product flow of interest from the region j to the region i, m_i denote the total product flow of region i, which includes domestic production from region i and imported product flow from other regions to region i. Let $\boldsymbol{h}$ denote by a n x 1 vector of h_i , representing the emission factors, i.e., regionalized impact for consuming one unit of product flow of interest in region i, $\boldsymbol{h^p}$ by a n x 1 vector of $h^p{}_i$, the total impact results of producing all product flow of interest in region i, for example, calculated by the approach suggested by Mutel and Hellweg (2009). $\boldsymbol{M}$ is a n x n diagonal matrix of $\widehat{m}$. $\boldsymbol{Z}$ is a n x n off-diagonal value of z_{ij}. The emission factor vector $\boldsymbol{h}$ can be calculated with the eq. (2.4). Further details of the model formulation are provided in the appendix 3.

$$\boldsymbol{h}=(\mathbf{M}-\mathbf{Z})^{-1}\boldsymbol{h^p} \tag{2.4}$$

The advantage of this model is that it is easy to implement requiring little data collection effort, especially when it comes to agricultural commodities and electricity product. The production and trade data are often provided by conventional statistics, such as FAOSTAT for main crop and food or ENTSO for electricity production, trade, and consumption information in Europe. When this model is compared with the model described by Kastner et al. (2011) and Qu et al. (2017b), the key difference is the relaxation of the emission assumption to include both direct and indirect impact, using $\boldsymbol{h^p}$ (the life cycle impact) to replace the impact from direct elementary flow impact. Thus, it integrates the benefit of flow tracing and the previously omitted "inter-industry linkage (the transaction of different processes in the tehnosphere matrix).

The applicability of this model is limited by the following conditions: first, it assumes there is no significant feedback loops between the studies system and its technology input. If product

2 also use product 1 as the main input, the $\boldsymbol{h^p}$ part obviously cannot be solved without taking into the flow tracing model of product 1. When this happens, the eq (2.4) is not valid. In the other words, this is applicable only when impact results h^p are independently from the flow tracing module. Secondly, it focuses on just analyzing one product. If the goal is to analyze multiple products simultaneously, it would not be convenient. To overcome these limitations, a generic integrated model for regionalized LCA is developed in section 2.5.2.

2.5.2 The general computational structure of process-based regionalized LCA

When there is perfect information available related to the sourcing production location of a product, the regionalized LCA can be easily computed by differentiating the regional difference the same as the differentiation of technology difference, as discussed by Yang and Heijungs (2017). In this article, we will not repeat that discussion. As described in Figure 2.1, when a buyer purchase or consumes the product 2 in a specific country; however, they do not know if the product 2 is 100% from the local production in that country or from the total supply in that country that includes both local production and foreign import from various countries. The focus is rather on the situation when the exact production location for a product is unknow.

Figure 2.2 demonstrates the structure of building the computation model for process-based regionalized LCA, with the key adaptations from the conventional site-generic LCA model summarized below: 1) following the same practice of ecoinvent, the transformation activity/ domestic production and market mix flow datasets that includes import and export are differentiated; 2) a site-generic product activity is disaggregated into product from multiple regions; 3) a trade balance module is introduced to make sure the supply of a market mix equals to the total import and domestic production supply in a region; this module also serves as the commodity flow tracing in the regionalized LCA model; 4) following the same treatment used in constructing the MRIO tables, the proportional sharing rule is used as the default assumption to construct the process-based regionalized LCA model, which assumes the export and domestic consumption share the same market mix without differentiating users in a region. This central assumption is also used by the developers of flow tracing models (Kastner, 2011; Qu et al. 2017b). The main reason is the data availability constraints of mapping data from specific producers to users.

For the matrix structure of the model, the differentiation of the regional difference and transformation processes (domestic production flow) / market processes (market mix flows) are not different from the differentiation of technology difference. Assuming the economy can

be categorized into n sectors, the supply matrix can be divided into two parts: we denote by $x^r{}_i$ the total production output of sector i in region r, by $\overline{x^r}_\iota$ the total market mix from sector i in region r.

The use matrix consists of four parts: the first two parts described the intermediate flows. We denote by $U^{rs}{}_{ij}$ the flow of domestic production product from sector i in region r to sector j from the transformation activities in region s (this term is often treated as zero as we don't know the exact production origin) , by $\widetilde{U^{rs}}_{\iota J}$the flow of market mix i in region r to the sector j in the transformation activities in region s (this term describe the intermediate flows or "inter-commodity relationship", which can be found from the conventional LCA database such as ecoinvent).

The second two parts describe the trade activities, and we denote by $\widetilde{U^{rs}}_\iota$ the flow of the domestic production product from the sector i in region r to market mix of the sector i in region s (this term is often a diagonal matrix), by $\overline{U^{rs}}_\iota$the flow of market mix i in region r to market mix i in region s, which can be obtained from the statistics that give bilateral trade matrix.

Let $f^r{}_i$ stands for he total final demand for sector i's domestic production product in region r, with a matrix form F, $\overline{f^r}_\iota$the total final demand of market mix i in region r, with a matrix form $\bar{F}$. Then, for the transformation processes and market mix, we have the following equations to describe the distribution of the product flows, respectively.

$$x^r{}_i = \sum_{r=1}^{p}\sum_{j=1}^{n} U^{rs}{}_{ij} + \sum_{s=1}^{p} \widetilde{U^{rs}}_\iota + \sum_{s=1}^{p} f^{rs}{}_i \tag{2.5}$$

$$\overline{x^r}_\iota = \sum_{r=1}^{p}\sum_{j=1}^{n} \widetilde{U^{rs}}_{\iota J} + \sum_{s=1}^{p} \overline{U^{rs}}_\iota + \sum_{s=1}^{p} \overline{f^{rs}}_i \tag{2.6}$$

The market mix i in region s, $\overline{x^s}_\iota$, is the sum of the import of both product i from transformation activities processes and product i from market mix from other regions plus the amount that is supplied domestically, as expressed in eq. (2.7). It is the sum of the elements in column market mix i in region s. The first term of the equation on the right is often treated as zero, as we don't know the product sourcing production origins. This term is similar to the total shipments of good i into the region s from all the regions described in eq. (3.18) from Miller and Blair (2009).

$$\overline{x^s}_\iota = \sum_{r=1}^{p} \widetilde{U^{rs}}_\iota \ (r \neq s) + \sum_{r=1}^{p} \overline{U^{rs}}_\iota \ (r \neq s) + \widetilde{U^{ss}}_\iota \tag{2.7}$$

				Transforming processes					Market processes						
				Product 1, activitiy	Product 1, activitiy	Product 1, activitiy	Product 1, activitiy	Product 2, activitiy	Product 1, market mix	Product 1, market mix	Product 1, market mix	Product 1, market mix	Product 2, market mix	Final use	Total
		Unit	Region	A	B	C	D	E	A	B	C	D	E		
Make matrix (Supply)	Product 1, activity	kg	A	200											200
	Product 1, activity	kg	B		1000										1000
	Product 1, activity	kg	C			100									100
	Product 1, activity	kg	D				10								10
Product	Product 2, activity	kg	E					1000							1000
	Product 1, market mix	kg	A						500						500
	Product 1, market mix	kg	B							1000					1000
	Product 1, market mix	kg	C								550				550
	Product 1, market mix	kg	D									460			460
	Product 2, market mix	kg	E										1000		1000
Use matrix (sell)	Product 1, activity	kg	A						200						200
	Product 1, activity	kg	B							1000					1000
	Product 1, activity	kg	C								100				100
	Product 1, activity	kg	D									10			10
Product	Product 2, activity	kg	E										1000		1000
	Product 1, market mix	kg	A	20				10			50	50		370	500
	Product 1, market mix	kg	B		100			5			350	200		345	1000
	Product 1, market mix	kg	C			10		20	100			200		220	550
	Product 1, market mix	kg	D				1	200	200		50			9	460
	Product 2, market mix	kg	E	20	40	15	5	20						900	1000

Intervention flows

			A	B	C	D	E	A	B	C	D	E
Land use	m2a	A	33									
Land use	m2a	B		33								
Land use	m2a	C			11							
Land use	m2a	D				8						
Land use	m2a	E					100					

Characterization factors	Unit	Region	Value
Ecosystem impact CFs	point /m2a	A	10
Ecosystem impact CFs	point /m2a	B	2
Ecosystem impact CFs	point /m2a	C	50
Ecosystem impact CFs	point /m2a	D	1000
Ecosystem impact CFs	point /m2a	E	80

Figure 2.2 The supply and use table of interindustry flows of goods in a process-based regionalized LCA

The Make matrix describes the total output of product from each process with the main product on the diagonal of the matrix. The off-diagonal values are zero unless there are co-products or by-products. The Use matrix describes various input for producing a product. The final demand matrix f stands for the surplus product available for final (consumer) use.

Following the same approach of conventional make-use model in Appendix 2, if we denote by X the diagonal matrix of $x^s{}_i$ the total production output from transformation activity processes, $\bar{X}$ the diagonal matrix of $\overline{x^s{}_\iota}$ the market mix processes. The supply matrix of a regionalized LCA, denoted by V'^R, can be expressed in the equation (2.8) below.

$$V'^R = \begin{pmatrix} X & 0 \\ 0 & \bar{X} \end{pmatrix} \tag{2.8}$$

Likewise, the use matrix U^R can be represented by eq (2.9). Let matrix U stands for the matrix of the intermediate distribution from transformation activities to flows from transformation activities $U^{rs}{}_{ij}$; $\breve{U}$ stands for the matrix of the intermediate distribution from market mix to flows from transformation activities $\widetilde{U^{rs}{}_{\iota j}}$. Let $\widetilde{U}$ stands for the matrix of the distribution from transformation activities to market mix flows $\widetilde{U^{rs}{}_\iota}$; and $\bar{U}$ stands for the matrix of the distribution from market mix to flows from market mix $\overline{U^{rs}{}_\iota}$. The function unit F^R is expressed as in equation (2.10).

$$U^R = \begin{pmatrix} U & \widetilde{U} \\ \breve{U} & \bar{U} \end{pmatrix} \tag{2.9}$$

$$F^R = \begin{pmatrix} F & 0 \\ 0 & \bar{F} \end{pmatrix} \tag{2.10}$$

Let C^R denotes spatially differentiated characterization factors by location or spatial archetype; B^R stands for corresponding elementary flows from and to the biosphere / intervention matrix with the same nomenclature. Recall the same matrix formulation from eq. (2.19) to eq (2.27) for site-generic LCA in the Appendix 2, the equivalent version of regionalized LCA impact H^R can be formulated with the eq. (2.11) below:

$$H^R = (C^R B^R)\,(V'^R - U^R)^{-1} F^R \tag{2.11}$$

When assuming all domestic production transformation activities is part of the market mix flow, eq (2.11) can be re-written into eq (2.12), where $\bar{U}$ (trade matrix) can be easily obtained from trade statistics for most agricultural commodities. The illustration in Figure 2.2 follow this simplified structure. As in most cases, supplier-specific information for intermediates economic flows is often not known, the eq (2.12) would be the most used approach for modeling regionalized LCA using the market mix approach.

$$\text{H}= (C^R B^R)\,\left(\begin{pmatrix} X & 0 \\ 0 & \bar{U} + X \end{pmatrix} - \begin{pmatrix} 0 & X \\ \breve{U} & \bar{U} \end{pmatrix}\right)^{-1} F^R \tag{2.12}$$

The eq. (2.4) is equivalent to the special case of the model described in (2.12) when $\breve{U}$ is zero. The use of this model (2.12) is based on the following premises:

- The production information of a product is not known, and there is a need to model the sourcing production location. If a company knows exactly the sourcing product production origin, the market mix here would not be useful. Instead, they should specify in the function unit to link their final demand with corresponding transformation activities directly.
- To enforce the flow tracing function, the trade matrix and market mix should be properly modeled. The model should include all major partners from the global trade network for a selected focal commodity to avoid potential truncation errors suffered by the conventional process-based LCA approaches.

These premises generally hold for agricultural and energy product. The exact production location is often unknow, hence we can assume all trade and production activity flow are part of market mix flow. The production and trade data are also available on a detailed product level on the national or regional level. Hence, the model eq (2.12) introduced in this article can be used to integrate product flow tracing into the traditional product LCA framework and database, such as the ecoinvent (2018) and World Food Life Cycle Database.

2.6 Numeric examples

2.6.1 Model validation

The numeric example in Figure 2.2 is adapted from the case study from Kastner et al. (2011), used to illustrate the model developed in this thesis. Suppose there is an economic system involving two products, product 1 and product 2, for instance product 1 stands for seed cotton farming, and product 2 stands for diesel fuel input for tillage machine. Product 1 are produced and traded among 4 countries and product 2 is produced from just one country. By applying the eq (2.12), Table 2.3 shows the impact result for product 1 and 2 consumed in respective countries, separated by country of origins. For example, the consumption of product 1 from the mixed residual flow in country A will cause 281.9, 14.0, 170.8, 3367.4 and 260.6 points of environmental impact from the production of the product 1 in country A, B, C, D and the production of product 2 in country E, respectively. Each row in the Table 2.3 represents the distribution of impact from sourcing countries of production to countries of consumptions. As expected, the sum of each row equals to the total production impact for respective countries. Following the input-out economic theory (see Miller and Blair 2009), the total production

impact should equal to the total impact occurred due to the final consumption activities. In the other words, environmental impact is attributed by the final demand.

Table 2.3 The impact results for the market flow product 1 and product 2

	Country	Product 1 A	Product 1 B	Product 1 C	Product 1 D	Product 2 E	Total
Product 1	A	281.9	0.2	18.1	21.3	11.8	333.33
Product 1	B	14.0	25.6	12.6	11.0	3.4	66.67
Product 1	C	170.8	0.7	247.3	96.9	39.8	555.56
Product 1	D	3367.4	11.9	610.1	3647.8	696.1	8333.33
Product 2	E	260.6	125.8	128.2	103.6	7381.7	8000

2.6.2 Comparison of regionalized impact results under different assumptions

The previous studies (Kastner et al. 2011; Qu et al. 2017a; Yang and Heijungs 2017) show the regional impact results are potentially sensitive to the trade approaches. Suppose the baseline scenario in this study is based on perfect information with complete bilateral trade data, production and consumption data from the numerical example illustrated above. Table 2.4 shows six common alternative approaches of considering trade data and supply chain situations.

Table 2.4 Model configurations of regionalized LCA

Model assumptions	**Description**
1)Direct trade adjustment	It assumes the imported product 100% produced locally from the importing countries
2)Global production share	It assumes the percentage of sourcing country of production for imported product is the same as the production share of each country of the total global production output. For example, this is the assumption used by the "GLO" data sets in the ecoinvent
3) Global export share	It assumes the percentage of sourcing country of origin for imported product is the same as the export share of each country of the total global export. For example, the is assumption is used by the World Food Life Cycle Database
4)Missing trade data	Truncation errors of incomplete trade activities, by omitting part of trading partners. In this example, it assumes the omission of the import from C by country A and D, and the import from B by country C from the bilateral trade matrix for product 1
5)Net import	The bilateral trade data is not available; however, the net import or export data can be obtained. It assumes the import and export product with the same environmental properties by aggregating the bilateral information only consider the net import or export volume
6)Omission of supply chain	Truncation errors of incomplete system boundary due to the omission of part of economic flow inputs. In this example, it assumes the exclusion of the product 2

By applying the model eq (2.12), Table 2.5 shows the impact results of transformation activity flows normalized to the baseline scenario, and Table 2.6 shows the impact results of the market

mix flows normalized to the baseline scenario. It shows different trade assumptions have large influence for the estimation of environmental impact of both producing and consuming product 1 and product 2 in different countries. The estimation of the production of the product 2 could also be highly affected by the trade assumptions, as there is a feedback loop. In this case, the model eq (2.4) will be not applicable.

Table 2.5 Comparison of impact from transformation activity flows normalized to the baseline results

Product	**Product 1**	**Product 1**	**Product 1**	**Product 1**	**Product 2**
Region	A	B	C	D	E
Baseline	100%	100%	100%	100%	100%
1)Direct trade adjustment	**653%**	**1551%**	**545%**	125%	**1739%**
2)Global production share	93%	81%	95%	100%	93%
3)Global export share	**205%**	**373%**	**178%**	102%	**205%**
4)Missing trade data	133%	124%	125%	100%	133%
5)Net import	102%	104%	98%	100%	102%
6)Omission of supply chain	**41%**	103%	70%	**10%**	0%

Table 2.6 Comparison of impact from market mix flows normalized to the baseline results

Product	**Product 1**	**Product 1**	**Product 1**	**Product 1**	**Product 2**
Region	A	B	C	D	E
Baseline	100%	100%	100%	100%	100%
1)Direct trade adjustment	**3856%**	**1551%**	**2293%**	**223%**	**1739%**
2)Global production share	130%	**373%**	**158%**	113%	93%
3)Global export share	98%	81%	96%	99%	**205%**
4)Missing trade data	**187%**	124%	**401%**	**170%**	133%
5)Net import	102%	104%	**46%**	113%	102%
6)Omission of supply chain	**20%**	103%	**40%**	**15%**	0%

2.6.3 Case study: tracing the biodiversity loss from Swiss palm oil consumption

One of the most studied topics in LCA is to analyze the spatial explicit environmental impact of consuming agricultural commodities. In this section, the case study from Chaudhary et al. (2016) of estimating the biodiversity loss due to swiss consumption of palm oil is re-calculated with the model developed in this study. In the Chaudhary et al. (2016) study, two key assumptions are made: i) if a country produces the exported crop, then the land use occurred there; ii) if an exporting country does not produce the product, the imported quantity was allocated to the biggest producers of this product worldwide in the same proportion as their global export share (data from FAOSTAT). However, these assumptions are rather arbitrary. As illustrated in Table 2.6, the global export share approach might potentially lead to large

errors. I will demonstrate in this section how the proposed approaches in this study can be used to improve the understanding of the distant biodiversity loss of palm oil due to consumption activities.

Based on the production and trade data of palm oil are obtained from FAOSTAT for the year of 2011, Figure 2.3 visualize the global value chain of palm oil trade in 2011 The top 98% of global traded volume are included (cut-off=2%). The size of each node is defined by the degree of a vertex, which is the number of its adjacent edges (bilateral trading partners). The circle shape indicates countries with palm oil production, whereas the square shape indicates countries without palm oil productions. It shows countries in the same region tends to trade with each other. Some countries, like Netherlands, Germany, and Italy, are just "virtual" trading hubs which do not produce any palm oil, however, they are important agents in trading palm oils from the global value chain perspective. Table 2.7 shows the raw data of sourcing countries to Switzerland in percentage of total volume imported palm oil. Switzerland palm oil imports are 30% from Netherlands, 11% from Germany and 2% from Italy, although these countries do not produce palm oil.

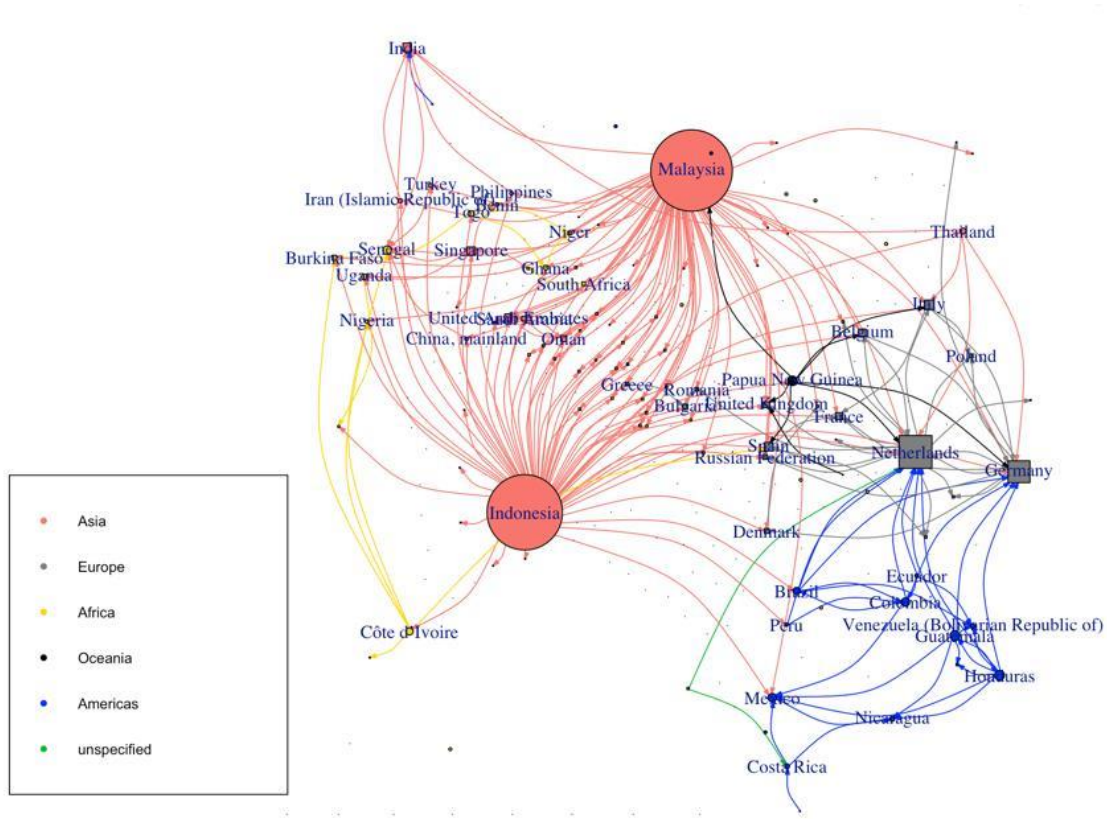

Figure 2.3 Global trade of palm oil in 2011 (cut-off: 2%)

Table 2.7 Comparison of the estimated sourcing country of origins and biodiversity loss for consuming 1 tonne of palm oil in Switzerland (FAOSTAT)

Country	**FAOSTAT**	**This study**	**Chaudary et al. 2016**	**Characterization factors**	**This study**	**Chaudary et al. 2016**
Year	2011	2011	2011		2011	2011
Unit	%	%	%	10 E-12 species eq. lost*year per ton	10 E-12 species eq. lost*year	
Netherlands*	30%					
Germany*	11%					
Italy*	2%					
Malaysia	21%	35%	38%	5.42	1.91	2.05
Indonesia	9%	31%	27%	4.66	1.45	1.24
Cambodia	**11%**	**9%**		1.82	0.16	0.00
Côte d'Ivoire	13%	12%	18%	3.16	0.38	0.57
Solomon Islands				5.97	0.00	0.00
Myanmar				2.17	0.00	0.00
Papua New Guinea		4%		5.97	0.24	0.00
Honduras		1%		6.96	0.05	0.00
Guatemala				7.78	0.00	0.00
Colombia		1%		8.64	0.10	0.00
United Republic of	**0.2%**	**0.1%**	**14%**			
Tanzania				0.45	0.00	0.07
Madagascar	2%		3%	0.13	0.00	0.00
Thailand		2%		1.62	0.03	0.00
Unspecified Area		3%		5.38	0.18	0.00
Ecuador		1%		15.60	0.08	0.00
Total Impact					***4.59***	***3.93***

By applying the equation (2.4) or (2.12), the distant biodiversity impact associated with palm oil consumed in Switzerland are calculated and compared with the estimation in the original study from Chaudhary et al. (2016), as presented in Table 2.7. Although both studies try to estimate the biodiversity loss occurred from country of productions due to swiss consumption of palm oil, several key difference can be observed: i) the palm oil imported from Cambodia based on the official data recorded the FAOSTAT accounts for 11% of the total Swiss palm oil import, however, this does not show up in the Chaudhary et al. (2016)'s data. The production volume of palm oil from Cambodia for the year of 2011 is missing from the raw FAOSTAT data. In this study, I took the production volume estimated by FAOSTAT for the year of 2013-2014 as a proxy. This yields 9% of palm oil imported by Switzerland comes from Cambodia, which is close to the 11% as reported by the official data reported by Switzerland as compiled by FAOSTAT. Note that not all palm oil imported from Cambodia are necessarily 100% from Cambodia, as Cambodia also imports palm oil from Malaysia and Indonesia. ii) Chaudhary et al. (2016) assumes 14% of palm oil are originally from United Republic of Tanzania based on

the global export share approach, although the FAOSTAT reports only 0.2% of palm oil imported by Switzerland is from Tanzania. This study can better reflect the reality and captures the palm oil impact from Papua New Guinea and Thailand hidden from the complex global value chain. iii) The difference of total impact from biodiversity loss from these two different approaches are non-negligible (4.59 vs 3.93).

2.7 Conclusion

In this study, different regionalized LCA approaches are reviewed, with their strengthens and weakness are discussed. A general matrix-based computational structure is developed for process-based regionalized LCA to improve the inclusion of spatial details of tracing the spatial locations of cross-border product flows along supply chains from production to consumption. It is validated with a numerical example and demonstrated with a case study from literature for an improved accuracy of impact results. Further comparison of several predominant assumptions used in process-based regionalized LCAs for deriving spatial location information are examined with numerical examples. Results show large variabilities of impact results and indicate the potential over- or under-estimation of impact results using those assumptions, including but not limited to the global production share, global export share, direct trade adjustment, and net import data. The proposed model in this chapter offers a coherent and transparent way of analyzing the influence from different trade assumptions or incomplete trade data and supply chain activities for a regionalized LCA analysis. It can be used to reduce the uncertainties associated with supply chain sourcing estimation introduced by arbitrary assumptions.

Appendix

Appendix 1. The Heijungs-Suh (HS) model for LCA

The standard matrix formulation for a product life cycle inventory is given by previous studies (Heijungs 1994; Heijungs and Suh 2013; Suh 2004; Suh and Huppes 2005). According to their approach, a life cycle inventory can be expressed as follow:

$$P = \left(\frac{A}{B}\right), Ps = \left(\frac{f}{G}\right) \tag{2.13}$$

It is defined by a $n \times n$ technology matrix $A = a_{ij}$, such as an element a_{ij}, shows inflows (negative sign) or outflows (positive sign) of commodity i of unit process j for a certain duration of process operation s, often for a country level or global level. For the associated $m \times n$ environmental intervention matrix $B = b_{kj}$, and b_{kj} denotes the amount of environmental elementary flow k emitted by unit process j during the operation time s that $a_{.j}$ is specified. The number of elementary flows covered by the environmental flow matrix B is given by m. Then commodity net output of the system is given by $f = f_i$, where y is the amount of a commodity delivered to outside of the system. And the environmental intervention for all possible functional flows is given by matrix G. Let entry of a column vector x shows the required process operation time of each process to produce the required net output of the system, assuming that processes at stake are being operated under a steady-state condition, so that selection of a specific temporal window for each process does not alter the relative ratio between elements in a column. We can deduct the following equations:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \ddots & a_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ a_{n1} & \cdots & a_{n(n-1)} & a_{nn} \end{bmatrix} s = \begin{bmatrix} f1 \\ f2 \\ \vdots \\ fn \end{bmatrix} \tag{2.14}$$

For simplicity, it can be rewritten into

$$As = f \tag{2.15}$$

The vector s can be calculated by

$$s = A^{-1}f \tag{2.16}$$

Similarly, for the environmental intervention matrix, we have

$$Bs = G$$

Substitute equation (2.16) into (2.16), the final environmental intervention matrix G can be calculated by multiplying the inverse of the technology matrix A with the environmental flow matrix and diagonalized vector of functional flows $\hat{f}$:

$$G = BA^{-1}\hat{f} = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \ddots & g_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ g_{m1} & \cdots & g_{m(n-1)} & g_{mn} \end{bmatrix} \tag{2.17}$$

Let C stands for the characterization factor matrix, where c_{lk} denotes the characterization factor associated with elementary flow k for the environmental indicator l. Let the matrix H stands for the life cycle impact results matrix, where h_{lj} denotes the impact results for the process j. The impact matrix H can be calculated with the formula (2.18)

$$H = CG = CBA^{-1}\hat{f} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1m} \\ c_{21} & c_{22} & \ddots & c_{2m} \\ \vdots & \ddots & \ddots & \vdots \\ c_{l1} & \cdots & c_{l(m-1)} & c_{lm} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \ddots & g_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ g_{m1} & \cdots & g_{m(n-1)} & g_{mn} \end{bmatrix} \tag{2.18}$$

Appendix 2. Constructing the LCA models based on the supply/Make-use framework

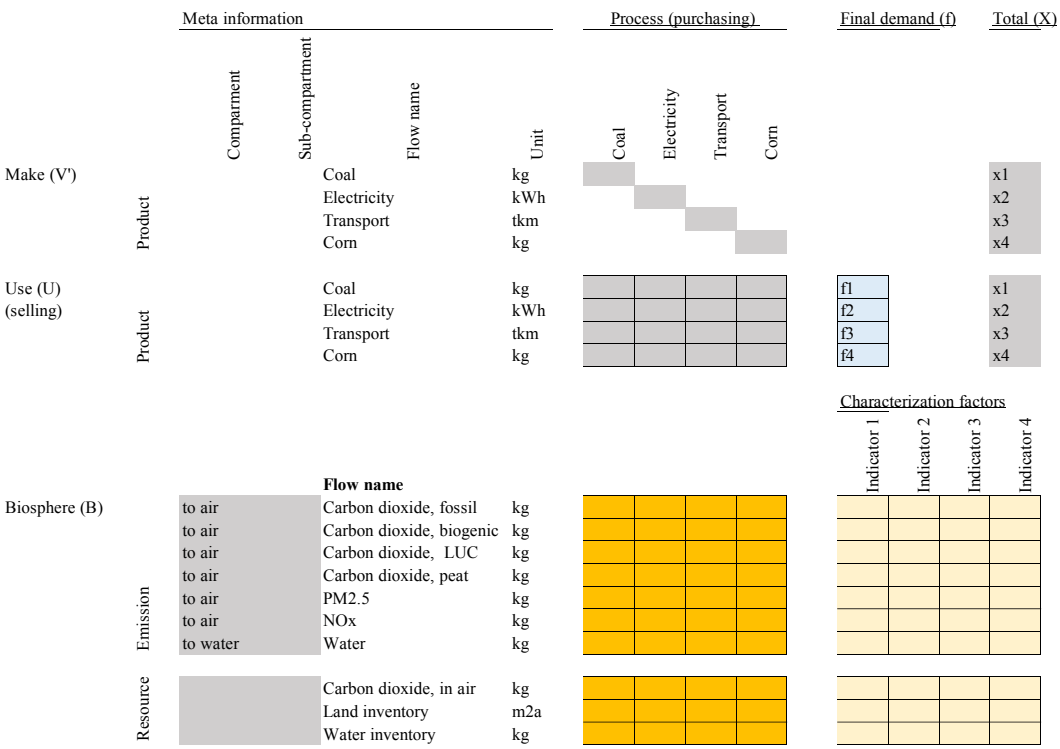

Figure 2.4 The supply and use table of interindustry flows of goods for site-generic LCA

The Make (V′) matrix describes the total output of product from each process with the main product on the diagonal of the matrix. The off-diagonal values are zero, unless there are co-products or by-products. The Use (U) matrix describes various

input for producing a product. The final demand matrix f stands for the surplus product available for final (consumer) use. The matrix should be ideally balanced (total output= use + final demand), complete (no truncation errors), and invertible. The biosphere (B) describe the environmental interventional flows. The matrix C includes the characterization factor for the elementary flows in the B matrix.

Assume that the economy can be categorized into n sectors. If we denote by x_i is the total output of sector i and by f_i the total final demand for sector i's product, eq. (2.19) describes sector i distributes its product through sales to other sectors and to final demand:

$$X_i = U_{i1} + \ldots + U_{ij} + \ldots + U_{in} + f_i = \sum_{j=1}^{n} U_{ij} + f_i \tag{2.19}$$

Let us use i to represent a column vector of 1's as a "summation" vector (see Miller and Blair 2009). The above equation can be re-written into eq. (2.20). Here **x** equals to the supply matrix $\mathbf{v}'$ in the supply-use framework.

$$\mathbf{x} = \mathbf{U}\mathbf{i} + \mathbf{f} = \mathbf{v}' \tag{2.20}$$

Once the technical coefficients is fixed, each U_{ij} on the right of (2.20) can be replaced with by a_{ij}/x_j, or rewritten into the equation (2.21) below.

$$\mathbf{A} = \mathbf{U}\hat{\mathbf{x}}^{-1} \tag{2.21}$$

With (2.21), the equation (2.20) can then be transformed into the equations below.

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{2.22}$$

$$(\mathbf{I}-\mathbf{A})\,\mathbf{x} = \mathbf{f} \tag{2.23}$$

$$\mathbf{x} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} \tag{2.24}$$

The total life cycle inventory emission matrix G can then be obtained with the (2.25)

$$\mathbf{G} = \widetilde{\boldsymbol{B}}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} = \mathbf{B}\,\hat{\mathbf{x}}^{-1}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} \tag{2.25}$$

With (2.21), the equation (2.25) can then be rewritten into the following:

$$\mathbf{G} = \mathbf{B}\,\hat{\mathbf{x}}^{-1}\,(\mathbf{I}-\mathbf{U}\hat{\mathbf{x}}^{-1})^{-1}\,\mathbf{f} = \mathbf{B}\,(\hat{\mathrm{X}}-\mathbf{U})^{-1}\mathbf{f} = \mathbf{B}\,(\mathrm{V}'-\mathbf{U})^{-1}\mathbf{f} \tag{2.26}$$

Let C stands for the characterization factor matrix, the life cycle impact results then can be computed with the formula below:

$$\mathbf{H} = \mathbf{C}\mathbf{B}\,(\mathrm{V}'-\mathbf{U})^{-1}\mathbf{f} = \boldsymbol{C}\widetilde{\boldsymbol{B}}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} \tag{2.27}$$

Appendix 3. Partial model: combine the flow-tracing model and LCA models

For the physical location-based consumption mix approach, the basic model described in eq (2.2) should be extended to consider the ratio of product flow from countries of origin to countries of consumptions. The latter can be estimated with the methods described in the literature (Li et al. 2013; Qu et al. 2017a,b ; Tranberg et al. 2019). For any region i, the total product flow m_i is the sum of the output from the domestic production, p_i, and imported flows from other regions. $Let\ z_{ij}$ represents the amount of product exported from the region j to the region i, c_i is the amount of consumption in region i. The eq (2.28) describe the mass balance.

$$m_i = p_i + \sum_{j=1}^{n} z_{ij} = c_i + \sum_{j=1}^{n} z_{ji} \tag{2.28}$$

$Let\ h_i$ stands for the emission factor we would like to compute for the region i due to consumption. Based on the proportionality share-rule rule, h_i represents the carbon footprint intensity of the total product flow m_i, which is the same for the c_i , the product consumed in region i, and z_{ji} the product exported from region i. Let p_{ki} stands for production output by technology k in region i, and $h^p{}_{ki}$ stands for the emission or impact intensity per unit which can be calculated using the eq (2.2). To balance the emission impact, the equation(2.28) can be rewritten into the equation (2.29)

$$h_i m_i = \sum_{k=1}^{n} h^p{}_{ki} \circ p_{k,i} + \sum_{j=1}^{n} h_j Z_{ij} \tag{2.29}$$

$Let\ z_i$ stands for the sum of all product flow exported into region i. $h^p{}_i$ is the sum of the impact of different production technology mode k in the region i based on production mix. By matrix transformation, the equation (2.29) can be simplified into the equation (2.30)

$$\begin{bmatrix} p_{1+Z1} & -z_{12} & \cdots & -z_{1n} \\ -z_{21} & p_{2+Z2} & \ddots & z_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ -z_{n1} & \cdots & z_{n(n-1)} & p_{n+Zn} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_n \end{bmatrix} = \begin{bmatrix} h^p{}_1 \\ h^p{}_2 \\ \vdots \\ h^p{}_n \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{n} h^p{}_{k1} \circ p_{k,1} \\ \sum_{k=1}^{n} h^p{}_{k2} \circ p_{k,2} \\ \vdots \\ \sum_{k=1}^{n} h^p{}_{kn} \circ p_{k,n} \end{bmatrix} \tag{2.30}$$

Let $\boldsymbol{h}$ stands for the n x 1 vector of h_i. $\boldsymbol{M}$ is a n x n diagonal matrix of $\widehat{m}$. $\boldsymbol{Z}$ is a n x n off-diagonal value of z_{ij}. $\mathbf{h^p}$ is a n x 1 vector of $h^p{}_i$. Eq. (2.30) can be summarized in eq. (2.31).

$$\mathbf{(M\text{-}Z)}*\boldsymbol{h} = \sum_{k=1}^{n} h^p{}_{ki} \circ p_{k,i} = \boldsymbol{h^p} \tag{2.31}$$

By solving the equation (2.31), the emission factor can be calculated using eq. (2.32)

$$\mathbf{h=(M\text{-}Z)^{-1}}\boldsymbol{h^p} \tag{2.32}$$

Reference

Ali AAM, Negm AM, Bady MF, Ibrahim MGE (2014) Moving towards an Egyptian national life cycle inventory database. Int J Life Cycle Assess 19:1551–1558. https://doi.org/10.1007/s11367-014-0760-z

Bengoa X, Chappuis C, Guignard C, et al (2020) World Food LCA Database Documentation. Version 3.5.1, January 2020. Quantis, Lausanne, Switzerland. World Food LCA Database http://www quantis-intl com/wfldb/files/WFLDB_MethodologicalGuidelines_v3 0 pdf

Bjelle EL, Többen J, Stadler K, et al (2020) Adding country resolution to EXIOBASE: impacts on land use embodied in trade. Economic Structures 9:14. https://doi.org/10.1186/s40008-020-0182-y

Borghi AD (2013) LCA and communication: Environmental Product Declaration. Int J Life Cycle Assess 18:293–295. https://doi.org/10.1007/s11367-012-0513-9

Boulay A-M, Bare J, Benini L, et al (2017) The WULCA consensus characterization model for water scarcity footprints: assessing impacts of water consumption based on available water remaining (AWARE). Int J Life Cycle Assess 1–11. https://doi.org/10.1007/s11367-017-1333-8

Braga TEN, Matsuura MI da SF, Dias FRT, et al (2018) Proposal for a collaborative LCA data management methodological aproach for creating “nodes” in the brazilian national inventory database (SICV) Brasil.

Brandão M, Levasseur A, Kirschbaum MUF, et al (2013) Key issues and options in accounting for carbon sequestration and temporary storage in life cycle assessment and carbon footprinting. Int J Life Cycle Assess 18:230–240. https://doi.org/10.1007/s11367-012-0451-6

Bulle C, Margni M, Patouillard L, et al (2019) IMPACT World+: a globally regionalized life cycle impact assessment method. Int J Life Cycle Assess 24:1653–1674. https://doi.org/10.1007/s11367-019-01583-0

Cardellini G, Valada T, Cornillier C, et al (2018) EFO-LCI: A New Life Cycle Inventory Database of Forestry Operations in Europe. Environ Manage 61:1031–1047. https://doi.org/10.1007/s00267-018-1024-7

CDP Home - CDP. https://www.cdp.net/en. Accessed 13 Jun 2018

Chaudhary A, Pfister S, Hellweg S (2016) Spatially Explicit Analysis of Biodiversity Loss Due to Global Agriculture, Pasture and Forest Land Use from a Producer and Consumer Perspective. Environ Sci Technol 50:3928–3936. https://doi.org/10.1021/acs.est.5b06153

Chomkhamsri K, Mungcharoen T, Yuvaniyama C (2017) 10-year experience with the Thai national LCI database: case study of “refinery products.” Int J Life Cycle Assess 22:1760–1770. https://doi.org/10.1007/s11367-016-1160-3

Colomb V, Amar SA, BASSET-MENS C, et al (2015) AGRIBALYSE, the French LCI database for agricultural products: high quality data for producers and environmental labelling. OCL Oilseeds and fats crops and lipids 22:D104. https://doi.org/10.1051/ocl/20140047

Court C, Jackson R (2015) Toward Consistent Cross-Hauling Estimation for Input-Output Regionalization. Regional Research Institute Working Papers

Durlinger B, Tyszler M, Scholten J, et al (2014) Agri-Footprint; a Life Cycle Inventory database covering food and feed production and processing. In: Proceedings of the 9th International Conference on Life Cycle Assessment in the Agri-Food Sector. pp 310–317

ecoinvent (2018) ecoinvent Version 3. https://www.ecoinvent.org/database/database.html. Accessed 1 Nov 2018

European Commission (2018) Single Market for Green Products - The Product Environmental Footprint Pilots - Environment - European Commission. http://ec.europa.eu/environment/eussd/smgp/PEFCR_OEFSR_en.htm#other_technical_information. Accessed 13 Jun 2018

Fantke P, Aurisano N, Bare J, et al (2018a) Toward harmonizing ecotoxicity characterization in life cycle impact assessment. Environmental Toxicology and Chemistry 37:2955–2971. https://doi.org/10.1002/etc.4261

Fantke P, Aylward L, Bare J, et al (2018b) Advancements in life cycle human exposure and toxicity characterization. Environmental health perspectives 126:125001

Fet AM, Skaar C, Michelsen O (2009) Product category rules and environmental product declarations as tools to promote sustainable products: experiences from a case study of furniture production. Clean Techn Environ Policy 11:201–207. https://doi.org/10.1007/s10098-008-0163-6

Finkbeiner M (2014) Product environmental footprint—breakthrough or breakdown for policy implementation of life cycle assessment? Int J Life Cycle Assess 19:266–271. https://doi.org/10.1007/s11367-013-0678-x

Hauschild MZ, Huijbregts M, Jolliet O, et al (2008) Building a Model Based on Scientific Consensus for Life Cycle Impact Assessment of Chemicals: The Search for Harmony and Parsimony. Environ Sci Technol 42:7032–7037. https://doi.org/10.1021/es703145t

Heijungs R (1994) A generic method for the identification of options for cleaner products. Ecological Economics 10:69–81. https://doi.org/10.1016/0921-8009(94)90038-8

Heijungs R, Suh S (2013) The Computational Structure of Life Cycle Assessment. Springer Science & Business Media

Heijungs R, Suh S (2002) The computational structure of life cycle assessment. Springer Science & Business Media

Hertwich EG, Gibon T, Bouman EA, et al (2015) Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies. PNAS 112:6277–6282. https://doi.org/10.1073/pnas.1312753111

Huijbregts MAJ, Steinmann ZJN, Elshout PMF, et al (2016) ReCiPe 2016: a harmonized life cycle impact assessment method at midpoint and endpoint level report I: characterization

Hull V, Liu J (2018) Telecoupling: A new frontier for global sustainability. Ecology & Society 23:

Ingwersen WW (2015) Test of US federal life cycle inventory data interoperability. Journal of Cleaner Production 101:118–121. https://doi.org/10.1016/j.jclepro.2015.03.090

Islam S, Ponnambalam SG, Lam HL (2016) Review on life cycle inventory: methods, examples and applications. Journal of Cleaner Production 136:266–278. https://doi.org/10.1016/j.jclepro.2016.05.144

ISO 14025 (2006) ISO 14025:2006 - Environmental labels and declarations -- Type III environmental declarations -- Principles and procedures. https://www.iso.org/standard/38131.html. Accessed 13 Jun 2018

Jolliet O, Frischknecht R, Bare J, et al (2014) Global guidance on environmental life cycle impact assessment indicators: findings of the scoping phase. Int J Life Cycle Assess 19:962–967. https://doi.org/10.1007/s11367-014-0703-8

Kastner T, Kastner M, Nonhebel S (2011) Tracing distant environmental impacts of agricultural products from a consumer perspective. Ecological Economics 70:1032–1040. https://doi.org/10.1016/j.ecolecon.2011.01.012

Lehmann A, Bach V, Finkbeiner M (2016) EU Product Environmental Footprint—Mid-Term Review of the Pilot Phase. Sustainability 8:92. https://doi.org/10.3390/su8010092

Lenzen M (2000) Errors in Conventional and Input-Output—based Life—Cycle Inventories. Journal of Industrial Ecology 4:127–148. https://doi.org/10.1162/10881980052541981

Lenzen M, Pade L-L, Munksgaard J (2004) CO2 Multipliers in Multi-region Input-Output Models. Economic Systems Research 16:391–412. https://doi.org/10.1080/0953531042000304272

Lesage P, Muller S (2017) Life Cycle Inventory: An In-Depth Look at the Modeling, Data, and Available Tools. Encyclopedia of Sustainable Technologies 267

Lesage P, Samson R (2016) Quebec Life Cycle Inventory Database Project : Using the ecoinvent database to generate, review, integrate, and host regional LCI data. international journal of life cycle assessment

Levasseur A, Lesage P, Margni M, et al (2010) Considering time in LCA: dynamic LCA and its application to global warming impact assessments. Environmental science & technology 44:3169–3174

Li B, Song Y, Hu Z (2013) Carbon Flow Tracing Method for Assessment of Demand Side Carbon Emissions Obligation. IEEE Transactions on Sustainable Energy 4:1100–1107. https://doi.org/10.1109/TSTE.2013.2268642

Liu XL, Wang HT, Chen J, et al (2010) Method and basic model for development of Chinese reference life cycle database. Acta Sci Circumst 30:2136–2144

Manfredi S, Allacker K, Pelletier N, et al (2015) Comparing the European Commission product environmental footprint method with other environmental accounting methods. Int J Life Cycle Assess 20:389–404. https://doi.org/10.1007/s11367-014-0839-6

Martínez-Blanco J, Inaba A, Finkbeiner M (2015) Scoping organizational LCA—challenges and solutions. Int J Life Cycle Assess 20:829–841. https://doi.org/10.1007/s11367-015-0883-x

Merciai S, Schmidt J (2018) Methodology for the Construction of Global Multi-Regional Hybrid Supply and Use Tables for the EXIOBASE v3 Database. Journal of Industrial Ecology 22:516–531. https://doi.org/10.1111/jiec.12713

Miller RE, Blair PD (2009) Input-output analysis: foundations and extensions. Cambridge university press

Minkov N, Schneider L, Lehmann A, Finkbeiner M (2015) Type III Environmental Declaration Programmes and harmonization of product category rules: status quo and practical challenges. Journal of Cleaner Production 94:235–246. https://doi.org/10.1016/j.jclepro.2015.02.012

Moran D, Wood R (2014) Convergence Between the Eora, Wiod, Exiobase, and Openeu's Consumption-Based Carbon Accounts. Economic Systems Research 26:245–261. https://doi.org/10.1080/09535314.2014.935298

Mutel C, Liao X, Patouillard L, et al (2019) Overview and recommendations for regionalized life cycle impact assessment. Int J Life Cycle Assess 24:856–865. https://doi.org/10.1007/s11367-018-1539-4

Mutel C, Liao X, Patouillard L, et al (2018) Overview and recommendations for regionalized life cycle impact assessment. Int J Life Cycle Assess. https://doi.org/10.1007/s11367-018-1539-4

Mutel CL, de Baan L, Hellweg S (2013) Two-Step Sensitivity Testing of Parametrized and Regionalized Life Cycle Assessments: Methodology and Case Study. Environ Sci Technol 47:5660–5667. https://doi.org/10.1021/es3050949

Mutel CL, Hellweg S (2009) Regionalized Life Cycle Assessment: Computational Methodology and Application to Inventory Databases. Environ Sci Technol 43:5797–5803. https://doi.org/10.1021/es803002j

Mutel CL, Pfister S, Hellweg S (2012) GIS-Based Regionalized Life Cycle Assessment: How Big Is Small Enough? Methodology and Case Study of Electricity Generation. Environ Sci Technol 46:1096–1103. https://doi.org/10.1021/es203117z

O'Rourke D (2014) The science of sustainable supply chains. Science 344:1124–1127. https://doi.org/10.1126/science.1248526

Patouillard L, Bulle C, Querleu C, et al (2018) Critical review and practical recommendations to integrate the spatial dimension into life cycle assessment. Journal of Cleaner Production 177:398–412. https://doi.org/10.1016/j.jclepro.2017.12.192

Peano L, Lansche J, Nemecek T (2012) THE WORLD FOOD LCA DATABASE PROJECT: TOWARDS MORE ACCURATE FOOD DATASETS. 3

Pfister S, Bayer P (2014) Monthly water stress: spatially and temporally explicit consumptive water footprint of global crop production. Journal of Cleaner Production 73:52–62. https://doi.org/10.1016/j.jclepro.2013.11.031

Pfister S, Vionnet S, Levova T, Humbert S (2016) Ecoinvent 3: assessing water use in LCA and facilitating water footprinting. Int J Life Cycle Assess 21:1349–1360. https://doi.org/10.1007/s11367-015-0937-0

Pomponi F, Lenzen M (2018) Hybrid life cycle assessment (LCA) will likely yield more accurate results than process-based LCA. Journal of Cleaner Production 176:210–215. https://doi.org/10.1016/j.jclepro.2017.12.119

Poore J, Nemecek T (2018) Reducing food's environmental impacts through producers and consumers. Science 360:987–992. https://doi.org/10.1126/science.aaq0216

Potting J, Hauschild M (1997) Part II: spatial differentiation in life-cycle assessment via the site-dependent characterisation of environmental impact from emissions. The International Journal of Life Cycle Assessment 2:209

Potting J, Hauschild M (2006) Spatial Differentiation in Life Cycle Impact Assessment: A decade of method development to increase the environmental realism of LCIA. The International Journal of Life Cycle Assessment 11:11–13. https://doi.org/10.1065/lca2006.04.005

Qu S, Li Y, Liang S, et al (2018) Virtual CO2 Emission Flows in the Global Electricity Trade Network. Environ Sci Technol 52:6666–6675. https://doi.org/10.1021/acs.est.7b05191

Qu S, Liang S, Xu M (2017a) CO2 Emissions Embodied in Interprovincial Electricity Transmissions in China. Environ Sci Technol. https://doi.org/10.1021/acs.est.7b01814

Qu S, Wang H, Liang S, et al (2017b) A Quasi-Input-Output model to improve the estimation of emission factors for purchased electricity from interconnected grids. Applied Energy 200:249–259. https://doi.org/10.1016/j.apenergy.2017.05.046

Quantis (2018a). World Apparel & Footwear LCA Database. In: Quantis. https://quantis-intl.com/tools/databases/waldb-apparel-footwear/. Accessed 13 Jun 2018

Quantis (2018b) Measuring Fashion environmental impact report. In: Quantis. https://quantis-intl.com/measuring-fashion-report-2018/. Accessed 1 Nov 2018

Reale F, Cinelli M, Sala S (2017) Towards a research agenda for the use of LCA in the impact assessment of policies. Int J Life Cycle Assess 22:1477–1481. https://doi.org/10.1007/s11367-017-1320-0

Reinhard J, Zah R, Hilty LM (2017) Regionalized LCI Modeling: A Framework for the Integration of Spatial Data in Life Cycle Assessment. In: Advances and New Trends in Environmental Informatics. Springer, Cham, pp 223–235

Rosenbaum RK, Anton A, Bengoa X, et al (2015) The Glasgow consensus on the delineation between pesticide emission inventory and impact assessment for LCA. Int J Life Cycle Assess 20:765–776. https://doi.org/10.1007/s11367-015-0871-1

Rosenbaum RK, Bachmann TM, Gold LS, et al (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. https://doi.org/10.1007/s11367-008-0038-4

Schmidt H-J (2009) Carbon footprinting, labelling and life cycle assessment. The International Journal of Life Cycle Assessment 14:6–9. https://doi.org/10.1007/s11367-009-0071-y

Sonnemann G, Vigon B (2011) Global guidance principles for Life Cycle Assessment (LCA) databases: a basis for greener processes and products

Sonnemann G, Vigon B, Rack M, Valdivia S (2013) Global guidance principles for life cycle assessment databases: development of training material and other implementation activities on the publication. Int J Life Cycle Assess 18:1169–1172. https://doi.org/10.1007/s11367-013-0563-7

Stadler K, Wood R, Bulavskaya T, et al (2018) EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. Journal of Industrial Ecology 22:502–515. https://doi.org/10.1111/jiec.12715

Suh S (2004) Functions, commodities and environmental impacts in an ecological–economic model. Ecological Economics 48:451–467. https://doi.org/10.1016/j.ecolecon.2003.10.013

Suh S, Huppes G (2005) Methods for Life Cycle Inventory of a product. Journal of Cleaner Production 13:687–697. https://doi.org/10.1016/j.jclepro.2003.04.001

Suh S, Leighton M, Tomar S, Chen C (2016) Interoperability between ecoinvent ver. 3 and US LCI database: a case study. Int J Life Cycle Assess 21:1290–1298. https://doi.org/10.1007/s11367-013-0592-2

Suh S, Lenzen M, Treloar GJ, et al (2004) System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. Environ Sci Technol 38:657–664. https://doi.org/10.1021/es0263745

Suh S, Weidema B, Schmidt JH, Heijungs R (2010) Generalized Make and Use Framework for Allocation in Life Cycle Assessment. Journal of Industrial Ecology 14:335–353. https://doi.org/10.1111/j.1530-9290.2010.00235.x

Tharumarajah A, Grant T (2006) Australian national life cycle inventory database: moving forward. In: In Proceedings of the 5th ALCAS Conference, Melbourne, Australia. Citeseer

The Federal LCA Commons (2020) Life Cycle Assessment Commons. https://www.lcacommons.gov/. Accessed 30 Jun 2020

Thinkstep (2018) GaBi Databases: GaBi Software. http://www.gabi-software.com/international/databases/gabi-databases/. Accessed 1 Nov 2018

Tranberg B, Corradi O, Lajoie B, et al (2019) Real-time carbon accounting method for the European electricity markets. Energy Strategy Reviews 26:100367. https://doi.org/10.1016/j.esr.2019.100367

Tufvesson LM, Tufvesson P, Woodley JM, Börjesson P (2013) Life cycle assessment in green chemistry: overview of key parameters and methodological concerns. Int J Life Cycle Assess 18:431–444. https://doi.org/10.1007/s11367-012-0500-1

Tukker A, Huppes G, Guinée J, et al (2006) Environmental Impact of Products (EIPRO): Analysis of the life cycle environmental impacts related to the final consumption of the EU-25. EUR 22284 EN. Brussels: European Commission Joint Research Centre

Tukker A, Koning A de, Owen A, et al (2018) Towards Robust, Authoritative Assessments of Environmental Impacts Embodied in Trade: Current State and Recommendations. Journal of Industrial Ecology 22:585–598. https://doi.org/10.1111/jiec.12716

UNEP (2011) Global guidance principles for life cycle assessment databases: a basis for greener processes and products : "Shonan guidance principles." United Nations Environment Programme, Nairobi, Kenya

UNEP (2017) Global Guidance for Life Cycle Impact Assessment Indicators Volume 1. In: Life Cycle Initiative. https://www.lifecycleinitiative.org/training-resources/global-guidance-lcia-indicators-v-1/. Accessed 12 Mar 2018

UNEP (2019) Global Guidance for Life Cycle Impact Assessment Indicators Volume 2

Verones F, Hellweg S, Antón A, et al (2020) LC-IMPACT: A regionalized life cycle damage assessment method. Journal of Industrial Ecology n/a: https://doi.org/10.1111/jiec.13018

Verones F, Pfister S, Zelm R van, Hellweg S (2017) Biodiversity impacts from water consumption on a global scale for use in life cycle assessment. Int J Life Cycle Assess 22:1247–1256. https://doi.org/10.1007/s11367-016-1236-0

Vionnet S, Lessard L, Offutt A, et al (2012) Quantis water database–technical report. Quantis International Lausanne, Switzerland Available via Quantis International: http://www quantis-intl com/waterdatabase php Accessed 2:

Wiedmann T (2009) A review of recent multi-region input–output models used for consumption-based emission and resource accounting. Ecological Economics 69:211–222. https://doi.org/10.1016/j.ecolecon.2009.08.026

Wood R, Stadler K, Bulavskaya T, et al (2015) Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability 7:138–163. https://doi.org/10.3390/su7010138

Yang Y (2016) Toward a more accurate regionalized life cycle inventory. Journal of Cleaner Production 112:308–315. https://doi.org/10.1016/j.jclepro.2015.08.091

Yang Y, Heijungs R (2017) A generalized computational structure for regional life-cycle assessment. Int J Life Cycle Assess 22:213–221. https://doi.org/10.1007/s11367-016-1155-0

3 Large-scale regionalized LCA shows that plant-based fat spreads have a lower climate, land occupation and water scarcity impact than dairy butter

In light of the sustainable diet debate, we conducted a large-scale regionalized LCA to answer the following questions: (i) does the climate advantage hypothesis of plant-based fat spreads and creams over dairy butter and cream hold regardless of the variabilities of product recipes, geographies and the influence of land use change (LUC)? A framework for operationalizing a large-scale regionalized LCA analysis was developed and applied to compare the environmental impacts of 212 plant-based fat spreads, 16 plant-based creams and 40 dairy alternatives sold in 21 countries per 1 kg of product. Results show all plant-based spreads had a significantly lower climate impact than butter, with and without LUC inclusion. The regionalized analysis highlighted large variabilities across products, ranging from 0.98 to 6.93 (mean 3.3) kg CO2-eq for 212 plant-based spreads and 8.08 to 16.93 (mean 12.1) kg CO2-eq for 21 dairy butter with 95th confidence interval. This research offers a framework for performing regionalized agricultural LCA for a large portfolio of products thereby enabling identification of inter-product variabilities and hotspots for the development of mitigation strategies. Key mitigation opportunities include reducing oilseed ingredients' embodied impacts by optimizing product recipe design and adapting supply chain sourcing and agricultural practice.

This chapter is based on the publication from Liao, X., Gerichhausen, M.J.W., Bengoa, X. *et al.* Large-scale regionalized LCA shows that plant-based fat spreads have a lower climate, land occupation and water scarcity impact than dairy butter. *Int J Life Cycle Assess* **25,** 1043–1058 (2020). https://doi.org/10.1007/s11367-019-01703-w

3.1 Introduction

Food production is estimated to be the largest cause of global environmental change, and the food sector is responsible for up to 30% of global greenhouse gas emissions (Vermeulen et al. 2012). Replacing production and consumption of animal-based food sources by plant-based alternatives could be a way to reduce the current impact of food production (Ranganathan et al. 2016; Poore et al. 2018; Willett et al. 2019). Previous studies show that the production of some plant-based spreads (seven products in UK, Germany and France) have lower climate change impacts and less land use compared with dairy butter (Nilsson et al. 2010; Milà i Canals et al. 2013); however, several critical gaps remain to fully understand the environmental performance between large variety of plant-based spreads and dairy butters sold in broad consumer markets. Firstly, a large spatial heterogeneity in environmental impacts may exist when producing the same agricultural products sourced from different producers and locations, with different agricultural practices (Poore et al. 2018) and embedded natural variabilities in different locations (Hellweg and Milà i Canals 2014); thus, there is a need to consider more geographies than the three country markets that were included in the earlier study. Furthermore, plant-based fat spreads sold in different countries have various product recipe design influenced by consumer preferences, packaging choices and supply chain logistics; however, these product-specific variabilities have not been comprehensively examined in terms of their influence on environmental impacts, from agricultural ingredient sourcing and production, through to processing, manufacturing, packaging, distribution, retailing, use and product end-of-life. Secondly, Poore et al. (2018) shows that the farm stage dominates GHG emissions from food, with most of them involving deforestation. Recent studies (Sandström et al. 2018; Pendrill et al. 2019) also find global agricultural commodity trade contributes to land use change (LUC) emission. The Nilsson study (Nilsson et al. 2010), comparing plant-based spreads and butter, only considered the GHG emissions from land use change (LUC) for a small selection of ingredients, such as palm oil; so the effect of comprehensively including LUC induced GHG emissions has yet to be considered. Thirdly, the available water remaining (AWARE) approach (Boulay et al. 2018) is recommended by the UNEP (UNEP 2016) and is also the default recommended method for assessing a water scarcity footprint by the Product Environmental Footprint Category Rules (PEFCR) Guidance (European Commission 2017). However, we did not find publications demonstrating an approach to operationalize regionalized LCA for a large portfolio of product recipes with complex agri-food supply chains for the same functionality, thus the feasibility of applying AWARE has yet to be tested. In light of the importance of the

sustainable diet debate (Willett et al. 2019; Poore et al. 2018; Ranganathan et al. 2016), in this study, we aimed to propose an operational framework for performing a large-scale regionalized LCA to answer the following questions: (i) does the climate advantage hypothesis of plant-based fat spreads and creams over dairy butter and cream hold regardless of the variabilities of product recipes, geographies and the influence of inclusion of greenhouse gas (GHG) emissions from LUC)? (ii) Considering the climate-water-land nexus (Ringler et al. 2013; Kraucunas et al. 2015; Conway et al. 2015), is there a risk of shifting impacts from climate to water scarcity and land occupation, and what are the key opportunities for impact mitigation?

3.2 Methods

The LCA method aims to compare the environmental impacts of the production of dairy butter and creams with plant-based alternative products using a standard attributional approach as per the PAS 2050 (BSI 2012), aligning with the latest international standards for dairy products, published by the International Dairy Federation (IDF 2015) and the European Dairy Association (EDA 2016). This study is not intended for investigating a large-scale change of the two systems nor long-term consequences of a decision to switch from one system to another. For the butter (or Nordic dairy spreads) vs plant-based fat spreads comparison, the functional unit (FU) was 1 kg of product (fresh matter) for spreading, baking or shallow frying, at consumer level. For the dairy cream vs plant-based cream comparison, the FU was 1 kg product (fresh matter) for whipping or cooking, at consumer level. The choice of FU is discussed further in the sensitivity analysis section. To address the research questions above, we developed a regionalized LCA framework to consistently assess a large portfolio (228 plant-based spreads/creams and 40 diary alternatives (see the Annex, S3.1 for the definition of terminology)) of product recipes sold in 21 countries based on primary data from Upfield (previously Unilever's margarine business). The methodological framework is presented in Figure 3.1, illustrating the main procedural steps, which is inherently iterative. It starts from goal and scope definition, which define the objectives, product systems, data quality requirement and cut-off criteria, as well as spatiotemporal context. In this study, the goal and scope define the overall data quality requirement using "minimal significance level" based on expert judgement for the difference of comparative study results to be considered as significant (see Annex 3. Table S3 for minimal significance level definition). It further defines data quality requirement using pedigree scores See the Annex Table S6 for key processes (notably agricultural oilseeds LCI datasets) identified through the gap and prioritization process, which further involved

sensitivity analysis of choices related to allocation, models and assumptions together with parameter uncertainty analysis. Results obtained from each step are evaluated against the predefined data quality requirement. In terms of spatial scope definition, the regionalized LCA conducted was required at the country scale for key life cycle stages. It includes variations in product recipes, key agricultural ingredients' country of origin and corresponding country-specific agricultural practices and embedded natural variations (such as fertilization, tillage practice, irrigation, yield, climate, soil properties), production factories and energy mixes, as well as packaging designs, transportation distances and packaging materials' end-of-life. More detailed descriptions of each step are provided in the Annex.

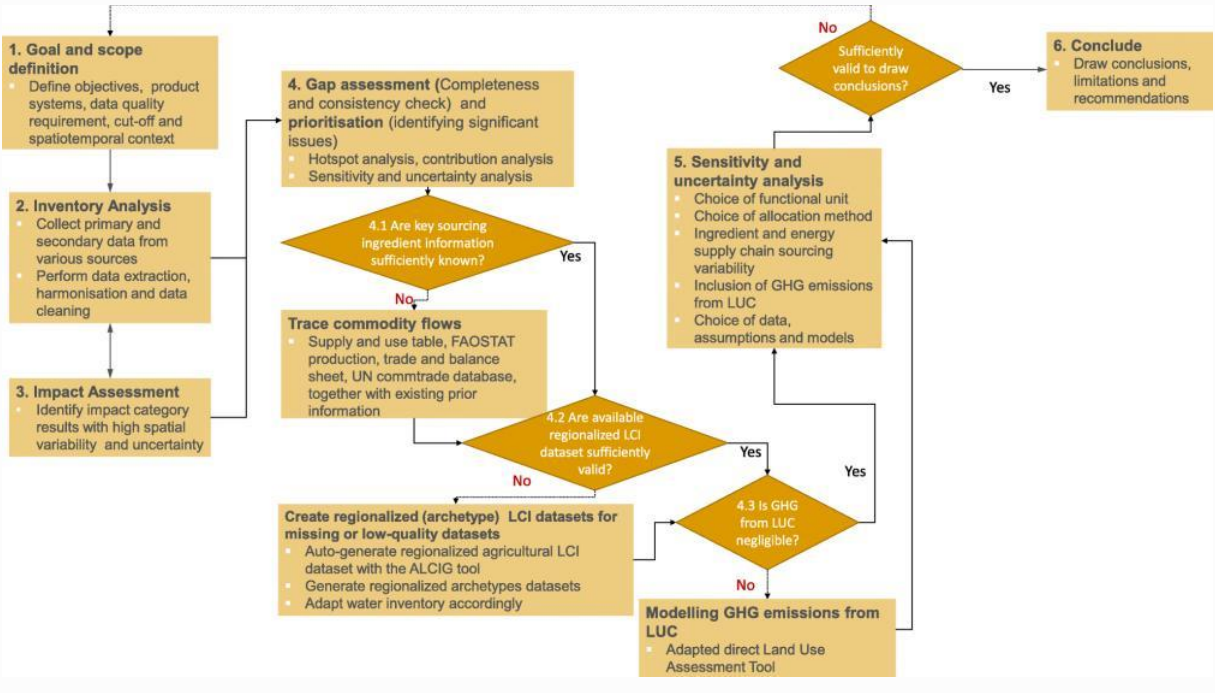

Figure 3.1 Methodological framework developed in the study

The following sections give further descriptions of product recipes, system boundaries, data collection, regionalization of supply chain, spatial (archetype) LCI development, treatment of LUC and water flow modeling, allocation procedures, sensitivity analyses and parameter uncertainty assessment for climate change results.

3.2.1 Products studied

A total of 228 plant-based spreads/creams are assessed. Of them, 201 had no butter fat and 27 were blended with a small amount of butter fat (less than 18%). For products used mainly for spreading and for baking or shallow frying, we assessed 212 predominately plant-based spreads

with different levels of fat and types of packaging, sold in 21 markets in Europe and North America. The plant-based spreads were compared with local butter substitute. Additionally, for Nordic countries, (Denmark, Finland and Sweden) the plant-based spreads were also compared to spreads with 40%, 60% and 75% dairy fat (containing no vegetable fat). Plant-based spreads are packaged in various tubs or wrappers of different shapes and volumes (dairy spread packaging is the same as plant-based spread tubs in Denmark, Finland and Sweden), whereas typical packaging for butter in Europe is aluminum foil laminated paper, or waxed paper in North America. For creams, used for whipping or cooking, we assessed 16 plant-based cream recipes and compared them with their dairy cream alternatives. Packaging formats used for plant-based creams are identical to that of dairy creams (polyethylene terephthalate (PET) bottle or liquid packaging board, depending on the market). The numbers of plant-based spreads/creams and their dairy substitute in each consumer markets are given in the Annex (Table S1 and Table S2).

3.2.2 System boundaries and cut-off

The LCA considered all identifiable activities across the product life cycle (cradle-to-grave) for all products in the 21 markets where they are sold (see Figure 3.2). Capital goods (ingredient delivery by trucks and ships, buildings, equipment, etc.) were included wherever data was available, such as for crop production, oil extraction and transformation and dairy processing. Capital goods at the distribution center and the point of retail were not included as the contributions of these processes to the total system's environmental impacts were expected to be less than 1%. The capital equipment and infrastructure processes from the ecoinvent database (v3.3) were used in the background system (Wernet et al. 2016). The following processes were left out of the system boundaries, consistent with attributional LCA practices: labor, commuting of workers, administrative work, cattle insemination and disease control. Food loss and food waste can take place at any stage in the products' life cycle. Statistical data at the national scale for specific product categories are not available and are therefore highly uncertain. At farm and processing level, losses are already accounted for in the processes' efficiency; therefore, uncertainty remains regarding food losses and waste during distribution, at retail point and at the consumer's home. There is no evidence showing different food losses and waste rates between plant-based spreads and butter (and between plant-based creams and dairy cream). Further, the PEFCR for Dairy Products (EDA 2016) does not require the inclusion of food waste in the assessment but rather suggests a waste rate of 7% for butterfat products, tested in a

sensitivity analysis. Food loss and waste during distribution, at retail point and at the consumer's home, is thus excluded from the scope of the study. Additional information is given in the Annex Table S4.

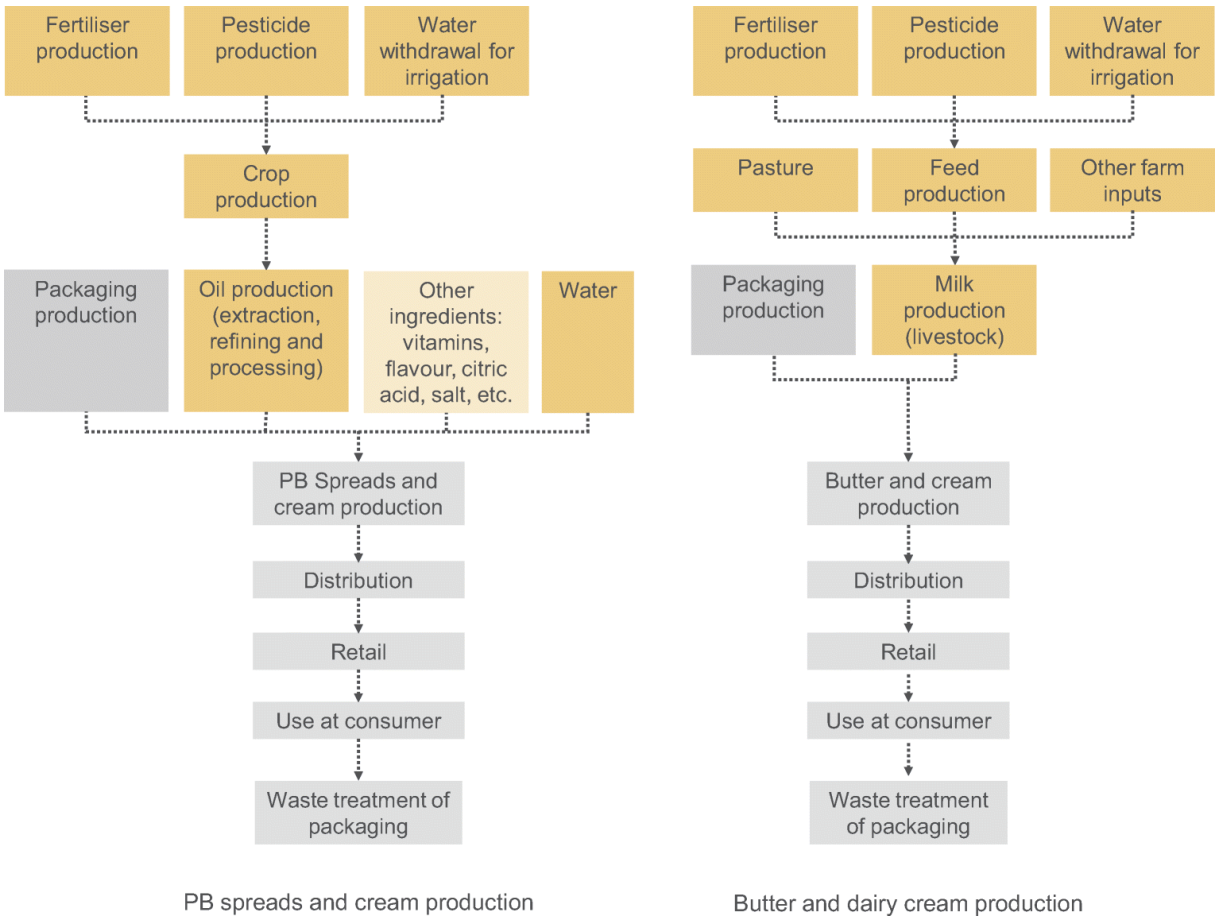

Figure 3.2 Schematic of the systems under evaluation

3.2.3 Environmental impact indicators considered

The assessment includes 15 environmental impact indicators from the European ILCD 2011 Midpoint+ v1.08 impact assessment method (JRC-IES 2011). Three additional indicators were included: land occupation (m^2/year), which reflects the total area of land used over one year and is a proxy for biodiversity and ecosystem services (Nemecek et al. 2011; Milà i Canals et al. 2012), water consumption (m^3), the total amount of fresh water consumed (ISO 14046), which includes, for example, evapotranspiration from irrigation water, and water scarcity footprint (m^3 water equivalent (eq)) based on the AWARE approach that assesses the water deprivation potential considering spatial water scarcity differences (Boulay et al. 2018). Additional information is given in the Annex Table S3.

3.2.4 Data sources, regionalization and spatial (archetype) LCI modeling

Primary data was collected from the manufacturer of the plant-based spreads and creams for all process stages within its control, namely recipe (i.e., ingredients and sourcing); oil processing where data is available e.g., from supplier or processing carried out by the manufacturer; product manufacturing; packaging materials weights and specifications; distribution transport distances from factories to markets. Secondary data was used to determine the bill of activities of other stages: crop production for oil crops and feed crops; raw milk production in each country; butter and cream production in each country; packaging materials and properties for butter and cream; distribution transport distances to point of sale (dairy products); storage at distribution center and at point of sale; use stage; packaging end-of-life. Main data sources are summarized in the Annex Table S4). The detailed modeling steps are given below, following the described framework in Figure 3.1.

3.2.4.1 Tracing agricultural commodity country of origin

Gap and prioritization analysis of the preliminary LCA results indicates that the most important data to be improved are spatial differentiations of agricultural ingredients. The modeling of crop-country combinations for agricultural ingredients is described below:

- Identification of crop sources and vegetable oil refining activities. When primary data of sourcing of country of origins were unavailable or incomplete (e.g., countries or regions are known, but exact quantities are unknown), the sourcing mix was based on average historical (2006-2011) FAOSTAT data for import and domestic production (country of origin and % sourcing). The model assumes that the final sourcing mix is proportional to the total of domestic and imported production volumes. A list of datasets accounting for parameters representative of average cultivation practices for each crop-country combination in the supply chain was developed for this study.
- Gap assessment for spatially differentiated LCI data development. The availability and quality of spatially differentiated country-level LCI datasets were evaluated according to crop sourcing information and data quality requirements. A list of missing data for further development are identified.
- Gap assessment for spatially differentiated elementary flows for impact assessment. Regionalized inventory data was further examined to evaluate the consistency with the requirements of the impact assessment methods. As a result, a customized version of ecoinvent v3.3 was developed to consistently support the AWARE method for the

water scarcity footprint. The assessment of the water scarcity footprint indicator requires particular attention to the consistent modeling of all life cycle inventory data, both in the foreground and background systems. In the present study, all foreground and background inventory data were adapted to ensure the following: Water flows in every process were properly balanced, which enabled calculation of the amount of water consumed as the difference between inputs and outputs. Water flows were all regionalized at country level as per the location where the withdrawals (inputs) and releases (outputs) were taking place, therefore enabling the association to the appropriate characterization factor.

- With key missing data identified, the sections below provide more details regarding generation of spatially differentiated (archetype) LCI datasets for plant-based and dairy products and the inclusion of GHG emissions from LUC.

3.2.4.2 Spatially differentiated LCI data generation for plant-based products

To conduct the gap assessment for plant-based spreads and plant-based creams, many of the regionalized LCI data were derived from the World Food LCA Database (WFLDB) v3.1 (Nemecek et al. 2015), which was updated with ecoinvent v3.3 data, system model "Allocation, cut-off by classification" (Weidema et al. 2013). The WFLDB was used as it provides unit process LCI data for many crops and countries, is representative of average production practices and includes data for dairy systems and processed food products.

For datasets with missing or low-quality data, additional LCI datasets were modelled using the Agricultural Life Cycle Inventory Generator (ALCIG) (Quantis 2016) consistent with the WFLDB approach for modeling the life cycle inventory of agricultural products (Nemecek et al. 2015). ALCIG calculates direct emissions at the farm, based on several customizable parameters such as input fertilizers and pesticides, soil type, climate conditions and farming practices (e.g., tillage). It integrates default values for most variables, based on statistical data from FAOSTAT, that can be used when specific data are not available. The ecoinvent database (v3.3) was used as a background database. Oil extraction and refining from agricultural oilseeds or crops are modelled based on data from Blonk Agri-footprint (2015) and Schau et al. (2016); separate LCI datasets were derived for crude oil extraction and refined oil production.

3.2.4.3 Spatial archetype LCI for dairy products

The spatial archetype-based approach was introduced to account for the variability of key parameters influencing the environmental footprint of raw milk, such as herd size, breed, feed composition, intensity (i.e., degree of mechanization) and manure management systems (MMS) in different countries. These parameters, except for the latter, influence the yield (i.e., kg raw milk per cow per year), the quality of the milk (i.e., fat and protein content) and direct emissions (through enteric fermentation and grazing) as well as the amount of manure to be managed. The dairy systems vary significantly between and within countries and therefore the approach applied by the WFLDB methodology guideline (Nemecek et al. 2015) was used to generate datasets representative of average raw milk production at a national scale. The country average dairy milk datasets are constructed in the following steps: firstly, 23 archetypes (or typologies) of milk production systems were modelled, based on the IFCN "typical farms" (FAO, IDF, IFCN 2014), and specific studies for USA (Thoma et al. 2013) and Canada (DFC 2012). They describe how cows are fed and tended to at the farm, representing a selection of the diversity of dairy systems considered in the study. Production systems were characterized by their size (i.e., number of lactating cows) and different feeding patterns (i.e., grazing or non-grazing; proportions of hay, grains and compound feed in rations). To be consistent with prior modeling approaches, emission models for different manure management systems were created based on IPCC (2006) emission factors for methane (CH_4), nitrous oxide (N_2O) and ammonia (NH_3). Six manure management systems are represented with up to three climate conditions (cool, temperate, warm). Each country has its own mix of manure management systems for dairy farming, as per FAO (2010a). Secondly, archetypes of typical dairy farms and MMS are combined in different proportions as to represent the typical dairy system mix in different countries. These mixes are mainly based on qualitative information retrieved from IDF and IFCN (FAO, IDF, IFCN 2014) and Eurostat 2013 data. All dairy farming modules generate milk as the main product, as well as live animals for slaughter or further fattening (i.e., male calves and culled cows) as co-products. The amount of milk produced is then corrected to a standard of 4% fat and 3.3% protein equivalent, according to the International Dairy Federation (IDF 2015) formula for fat and protein-corrected milk (FPCM). Additional detailed illustration and data are given in the Annex S3.2. Butter and cream processing data are based on EDA (2016), which provides typical data that can be used to represent average processing of dairy products. According to EDA (2016), the technology used in different countries is quite homogeneous, although higher variations are observable among large, small, and medium dairy

farms. WFLDB datasets combine these data with complementary information from literature (Nemecek et al. 2015; Djekic et al. 2014, Flysjö 2012) to generate comprehensive LCI datasets. To regionalize the processing step, the national milk mix and national electricity consumption mix are used. Butter processing results in two other co-products: skimmed milk and buttermilk.

3.2.4.4 Modeling GHG emissions from land use change

In crop production, global land transformation impacts are mainly driven by deforestation of primary forests. However, land use change (LUC) from deforestation of secondary forest or conversion from other types of land (grassland, perennial, or annual crops) to arable land are also addressed. In agricultural systems, LUC can be an important contributor to GHG emissions (Poore et al. 2018). In this study, country-specific GHG emissions due to land use and LUC are assessed for each relevant vegetable oil ingredient and dairy feed input. The LUC impact assessment follows the framework defined in ecoinvent v3 (Nemecek et al. 2014), which is based on IPCC (2006) methodology. Land inventory data are obtained at the national level per crop and per type of land use based on FAO data (FAOSTAT 2012, FAO 2010b). Land use changes are calculated over the period 1990–2010. The LUC modeling approach builds on the Direct Land Use Change Assessment Tool Version 2013.1 (Blonk Consultants 2013) and is compliant with PAS 2050-1 protocol (BSI 2012). The amortization of GHG emissions is 20 years, which is aligned with PAS 2050-1 (BSI 2012) and FAO guidelines for feed supply chains (LEAP 2015). It accounts for all carbon pools i.e., above-ground biomass (AGB), below-ground biomass (BGB), dead organic matter (DOM) and soil organic carbon (SOC) (Further data is provided in the Annex Table S5). The values for the relevant carbon pools were taken from the IPCC Agriculture, Forestry and Other Land Use report (IPCC 2006) and FAO (2010b), Annex 3, Table 11. Country climates and soil types were taken from the European Soil Data Centre (ESDAC 2010).

In this study, three major modifications were made to the original tool (Blonk Consultants 2013): (i) addition of the SOC-related emissions from peat drainage per hectare and year for pasture areas, using IPCC (2013) for emissions calculations, based on Joosten (2009) for the surface of forest grown on peatland in each country and emissions from peat degradation reported at the national scale for all countries in 2008; this adjustment is added because pasture is not included as a crop type and the degradation of drained peatland is not considered in the original Blonk tool; (ii) inclusion of carbon capture in vegetation when

relevant (e.g. when grassland is transformed into perennial cropland); (iii) addition of N_2O emissions related to SOC degradation according to IPCC (2006).

For climate change impacts from LUC, two allocation schemes corresponding to different "value systems" are considered: the "crop-specific" and "shared responsibility". The default allocation scheme used in this study is "crop-specific", while the "shared responsibility" approach is assessed in a sensitivity analysis.

- Crop specific: LUC is allocated to all crops and activities for which production area expanded over the last 20 years in a given country, according to their respective area increase.
- Shared responsibility approach: LUC during the last 20 years is evenly distributed among all crops and activities in the country, based on current area occupied.

3.2.5 Allocation procedures

A common methodological decision in LCA occurs when the system being studied produces co-products, such as vegetable oil and meal from oil extraction, or milk and meat from dairy farming. When systems are linked in this manner, the boundaries of the system of interest must be widened to include the system using all co-products, or the environmental impacts of producing the linked product must be attributed to the different co-products in the systems. Based on the Methodological Guidelines for Agricultural Products (Nemecek et al. 2015), economic allocation was used by default for crop co-products at the farm and processed oil seeds ingredients. For dairy milk, upstream burdens and activities were allocated to the raw fat and protein-corrected milk (FPCM), using the IDF formula (IDF 2015) and live animals based on biophysical criteria following the ISO hierarchy of allocation procedure (ISO 2006a, 2006b). For dairy butter and cream processing, the allocation of the upstream burden embodied in the raw milk as well as other inputs (energy, water, refrigerants) and outputs (wastewater, etc.) is based on the dry weight (i.e., dry matter content) of butter and cream and its co-products, following the IDF (2015) and the European PEF category rules for Dairy products EDA (2016). All transport was assumed to be weight-limited due to the high density of the ingredients (oils and raw milk) and final products. For all packaging recycling processes, in alignment with ecoinvent methodology, the "cut-off by classification" approach was used to allocate recycled content and recycling at end-of-life (Ekvall and Tillman 1997). The allocation method used for

background processes depends on the approach applied in the ecoinvent database. More details of allocation procedures and data are further elaborated in the Annex.

3.2.6 Sensitivity and uncertainty analysis

To ensure robustness of the LCA results, various sensitivity analyses were conducted in this project on the following key aspects: functional unit, LUC allocation approach, vegetable oils extraction allocation approach, worse case scenarios for supplying country of origins of main vegetable oils, packaging types and electricity production mix. To further improve robustness of climate change results, an uncertainty assessment has also been performed. Each product system is considered to include uncertainty with respect to (1) reference flows and (2) emission factors that are used to determine the LCI based on the reference flows. The parameter uncertainty is assessed with the Pedigree approach (Weidema et al. 2013). The total uncertainty of climate change results for butter and dairy cream is performed in SimaPro version 8.3 by running a Monte Carlo simulation of 1000 times. To assess the results' uncertainty of 228 plant-based spreads and plant-based creams, the analytical uncertainty propagation approach based on Taylor series expansion was used by adapting the uncertainty assessment method introduced by the GHG Protocol (2011). Results of sensitivity and uncertainty analysis are presented and discussed below in Section 3.3.

3.3 Results and discussion

For the LCA modeling tool, SimaPro version 8.3 was used to model individual datasets, such as oilseeds, required for plant-based products and the whole life cycle of dairy products. Data from all life cycle stages of plant-based spreads were aggregated and assessed in a customized modular Excel model to enable efficient sensitivity and uncertainty analyses for the large portfolio of product scenarios in this study. The detailed results and discussions are given below.

3.3.1 Plant-based spreads vs butter and dairy spreads

Figure 3.3 illustrates the probability density function of six main impact indicators comparing 211 plant-based spreads with 21 butters sold in 21 consumer markets, using the non-parametric kernel density estimation (KDE) approach (Wickham 2016). One plant-based fat spread with very extreme value is excluded from the plotting. As shown in Figure 3.3, large variabilities exist among product recipes. For 3 Nordic countries (Denmark, Finland, Sweden), dairy spreads are also studied. The comparison of plant-based spreads with dairy spreads and butter are shown in Figure 3.4. Additional information is given in the Annex Figs S1-S5.

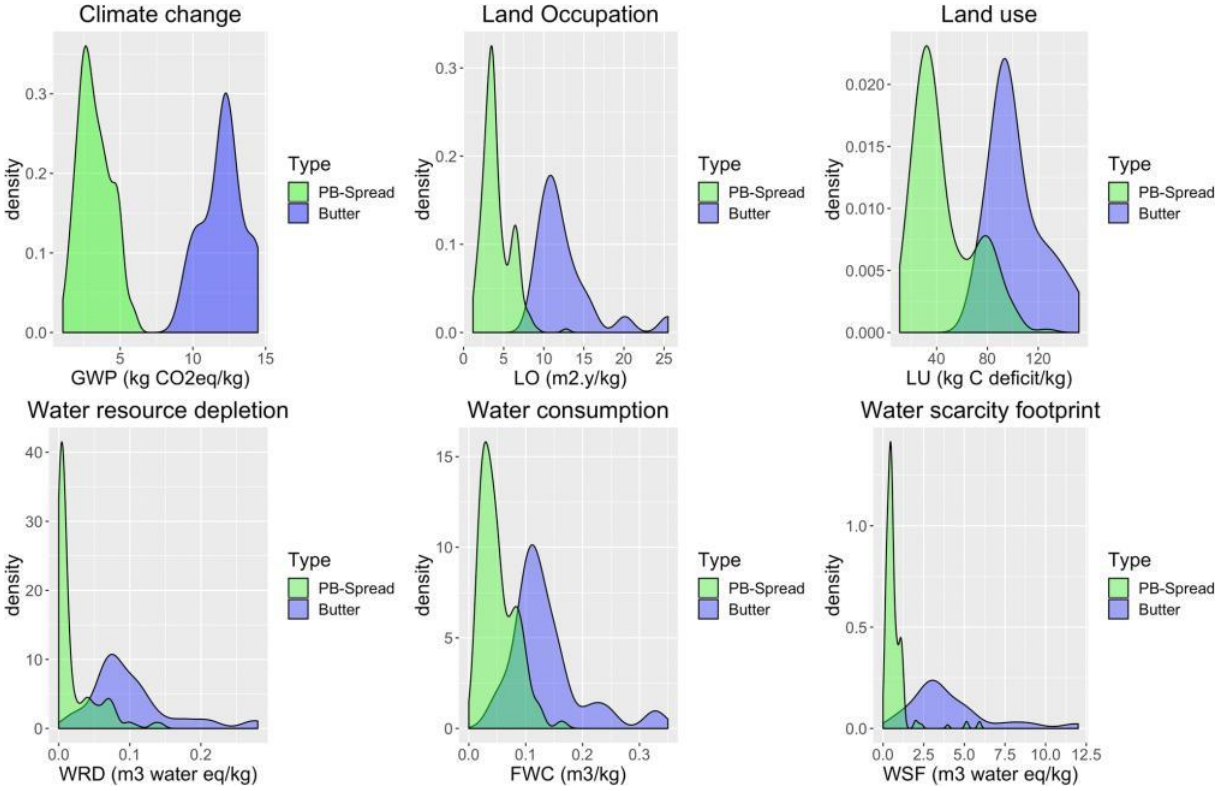

Figure 3.3 Comparing environmental impacts of plant-based spreads with butter in 21 countries

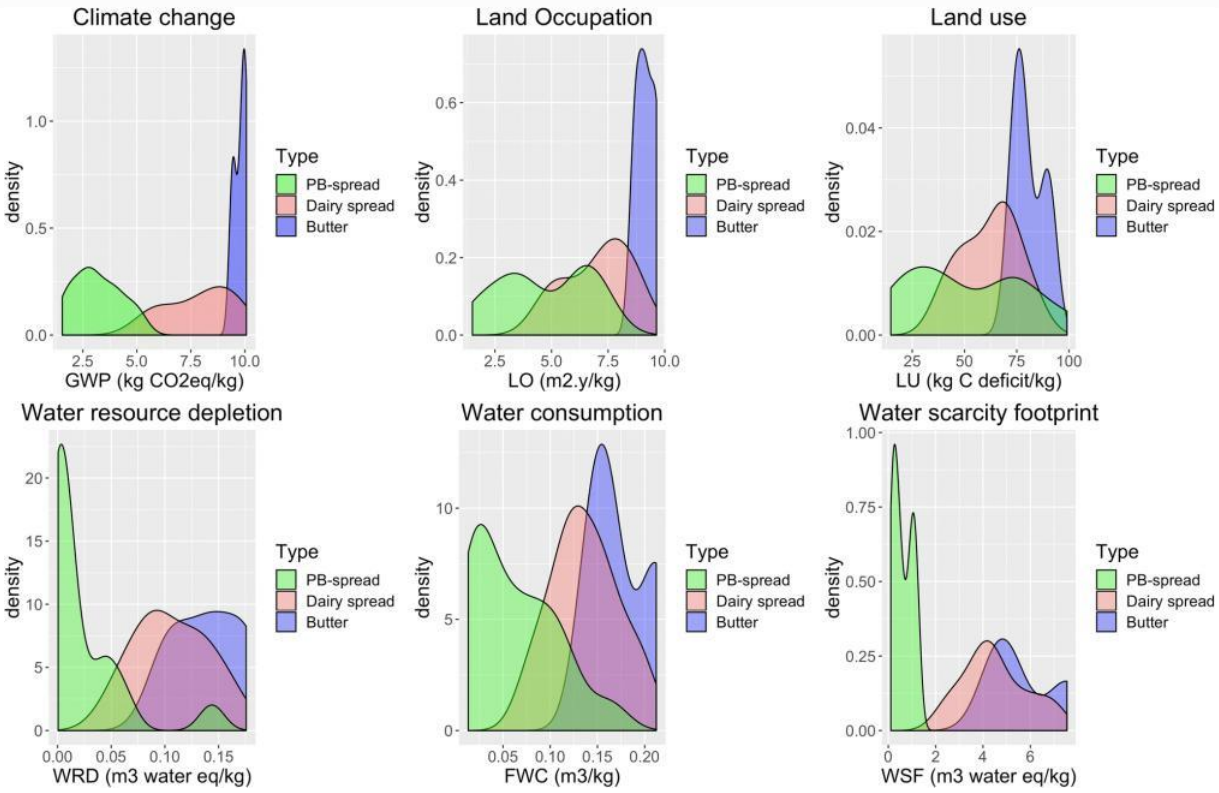

Figure 3.4 Comparing environmental impacts of plant-based spreads with butter and dairy spreads in three Nordic markets (Denmark, Finland and Sweden).

In statistics, kernel density estimation is a useful technique to visualize the shape based on finite data samples as in our study. The *x*-axis indicates the respective indicator results. The smaller the range of impact values of different products in *x*-axis, the higher the density value is. The integral of the shape for each type for a given impact indicator equals to 1, the 100% of probability. The detailed discussions are given below for key environmental impact indicators of interests.

3.3.1.1 Climate change impacts

Figure 3.3 shows overall that plant-based spreads (mean 3.3 kg CO2-eq) in the 21 markets studied have lower climate change impacts than butter (mean 12.1 kg CO2-eq); however, Figure 3.5 shows the regionalized LCA results highlighted large variabilities on the individual product level, driven by difference in product recipe design and spatial variabilities of sourcing ingredients. Further details on uncertainty analysis (Section 3.3.5) and the influence of spatial LUC emissions (Section 3.3.3) are discussed below. Figure 3.4 shows for the 7 dairy spreads on the Nordic markets in Denmark, Finland and Sweden, climate change impacts are highly correlated with fat content. For dairy spreads with the lowest fat content (40%, in Finland and Sweden) climate change impacts are similar to those of plant-based spreads with the highest climate change impacts of all plant-based spreads (also see detailed aggregated country results in Figure 3.9). However, when comparing plant-based spreads and dairy spreads sold in Finland and Sweden, climate change impacts are lower for the plant-based spreads.

When considering impacts per life cycle stage, Figure 3.5 shows on average the largest contributor for plant-based spreads is the production of the vegetable oil ingredients (2.24 kg CO_2-eq/kg, 68% of total climate change impacts); whereas for dairy butter, the production of raw milk is the main contributor for butter, contributing on average to 92% of total climate change impacts. Feed production and dairy farm activities such as methane emissions from enteric fermentation and manure management all contribute to climate change impacts. Packaging of plant-based spreads contributes 0.23 kg CO_2-eq/kg (7%); whereas for butter, packaging contributes on average 0.06 kg CO_2-eq/kg, which is less than 1% of total climate change impacts. This is due to differences in both the weight and type of packaging used with the butter being in lightweight paper either laminated in aluminum or waxed whereas the spreads are in heavier plastic tubs. Other notable difference includes production stage and distribution stage. Compared with plant-based fat spreads, dairy butter has higher production climate change impact, due to higher processing energy; on the other hand, it has lower climate

impact related to the distribution phase, as it has much shorter distance required to distribute final product to final consumers with freezing transportation.

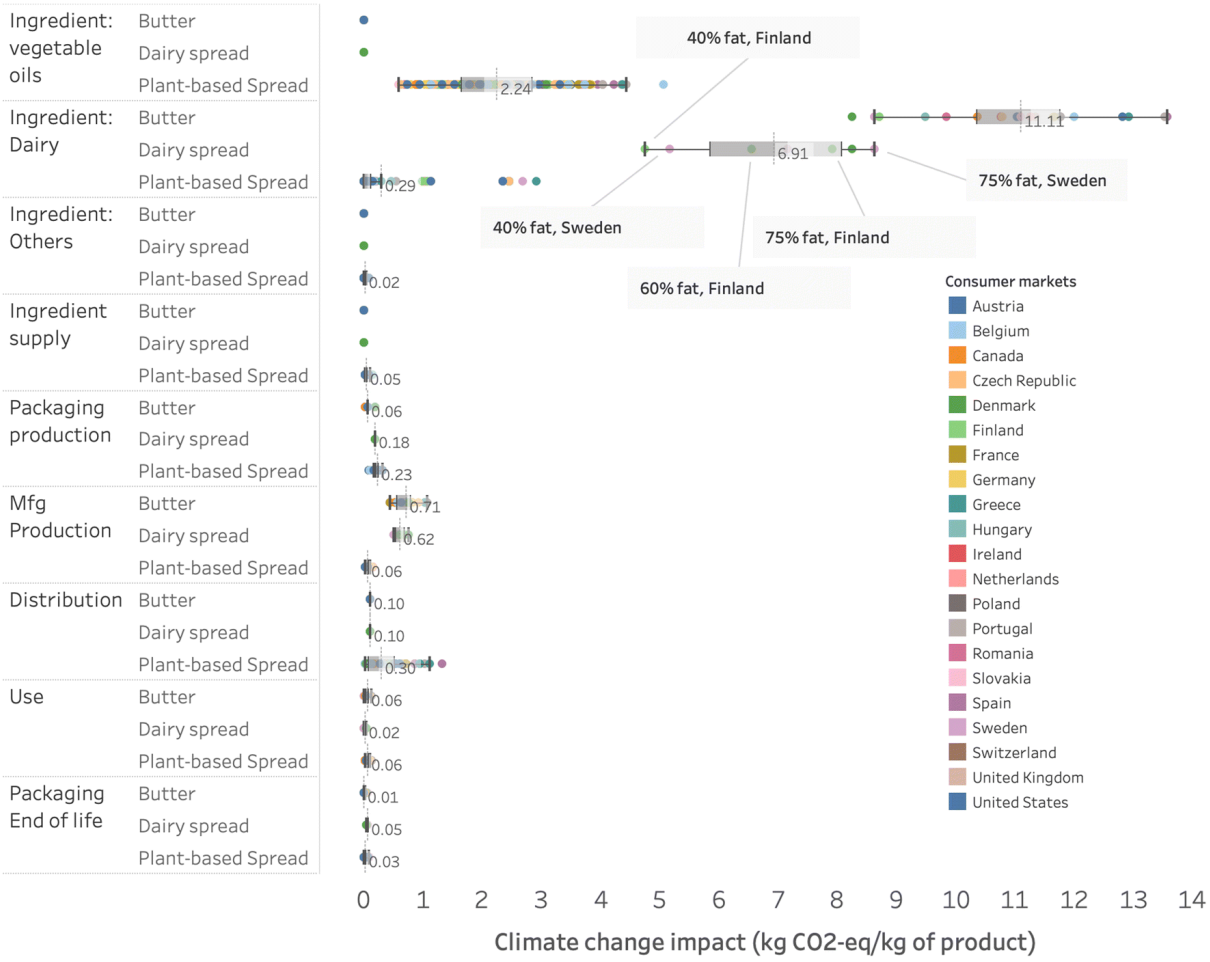

Figure 3.5 Impact on climate change of 212 plant-based fat spreads, 7 dairy spreads and 21 butters per kilogram by life cycle stage (the average values are shown in the figure)

3.3.1.2 Freshwater consumption, water scarcity footprint and water depletion potential

For freshwater consumption and water scarcity results, Figure 3.3 and Figure 3.4 show there are high variabilities across product recipes and markets, driven by differences in yield and irrigation of crops and orchards. Figure 3.4 shows there are overlaps, particularly between plant-based spreads and dairy spreads with low fat (e.g., 40%) levels, and between butter and dairy spreads with high fat (e.g., 75%) levels (See more details in Annex Fig. S3). This is because a higher fact content often leads to higher climate, water and land impacts, vice versa (See more details in the Annex, Fig. S1). In general, a linear relationship exists among solid content, fat content and calories (Nikolaou et al. 2016). A few exceptions of butters, notably in Ireland, have lower water consumption, due to embedded variabilities of dairy farming systems,

influenced by different herd structures, feed intake compositions and manure management systems. The dairy farming systems in Ireland have a relatively higher proportion of pasture, hay, silage, haylage and agricultural residues rather than grains and concentrated feed (More details are available in the Annex. S3.2 Spatial archetypes of dairy systems). For water scarcity footprint, most plant-based spreads (205 of 212 assessed) have a lower footprint in their respective consumer markets (see the Annex, Fig. S3), except for plant-based spreads containing dairy ingredients or oil seeds sourced from high water-stressed regions with low yields, such as olive oil from Tunisia.

3.3.1.3 Land occupation and land use

In terms of the surface areas required for land occupation, Figure 3.3 and Figure 3. 4 show there are some overlaps between plant-based spreads and dairy butter if the constraints of consumer countries are ignored. However, it is found that most plant-based spreads (211 of the 212) have lower impacts compared with butter in their respective consumer markets, while some overlaps are observed when compared with dairy spreads. When considering the land use indicator, measured by soil organic carbon (SOC), there are more overlaps in results between plant-based spreads and both butter and dairy spreads in general or in their respective consumer markets (Also see more details about country-specific comparisons in the Annex, Fig. S3).

Overall, when comparing plant-based spreads and dairy butter products, there is little risk of shifting climate impact to water and land related impact (See the Annex Fig. S1); however, special attention should be paid to agricultural ingredients from regions with high embodied land occupation or water scarcity footprint. There are opportunities for further reducing the environmental impact of plant-based fat spreads by e.g., adapting product recipes, opting for alternative agricultural oilseeds ingredients and/or adapting sourcing countries to avoid deforestation or other land use change–related climate risks. Meanwhile, it is also important to consider potential constraints, such as the choice of oils based on consumer preferences (taste, nutritional benefits and product function e.g., harder fats are used for products in warmer climates).

3.3.1.4 Other indicators

Plant-based spreads generally perform better than butter for several indicators including particulate matter, acidification and terrestrial eutrophication potentials, freshwater ecotoxicity,

and mineral, fossil and resource categories. For the other impact indicators, significant overlaps exist between plant-based spreads and butter (available in the Annex, Fig. S4).

3.3.2 Plant-based creams vs dairy creams

Figure 3.6 show the overall comparison of environmental impacts between plant-based creams and dairy creams in all 21 markets. For climate change, plant-based creams have lower climate change impacts compared with dairy creams, apart from those with very low-fat creams (15% fat). For the other impact indicators, there are no significant differences between plant-based creams and dairy creams. More details are also given in the Annex Fig. S3 for details classified by consumer markets, S6 for the full 18 impact indicators, Fig. S7 for climate impact breakdown by life cycle stages.

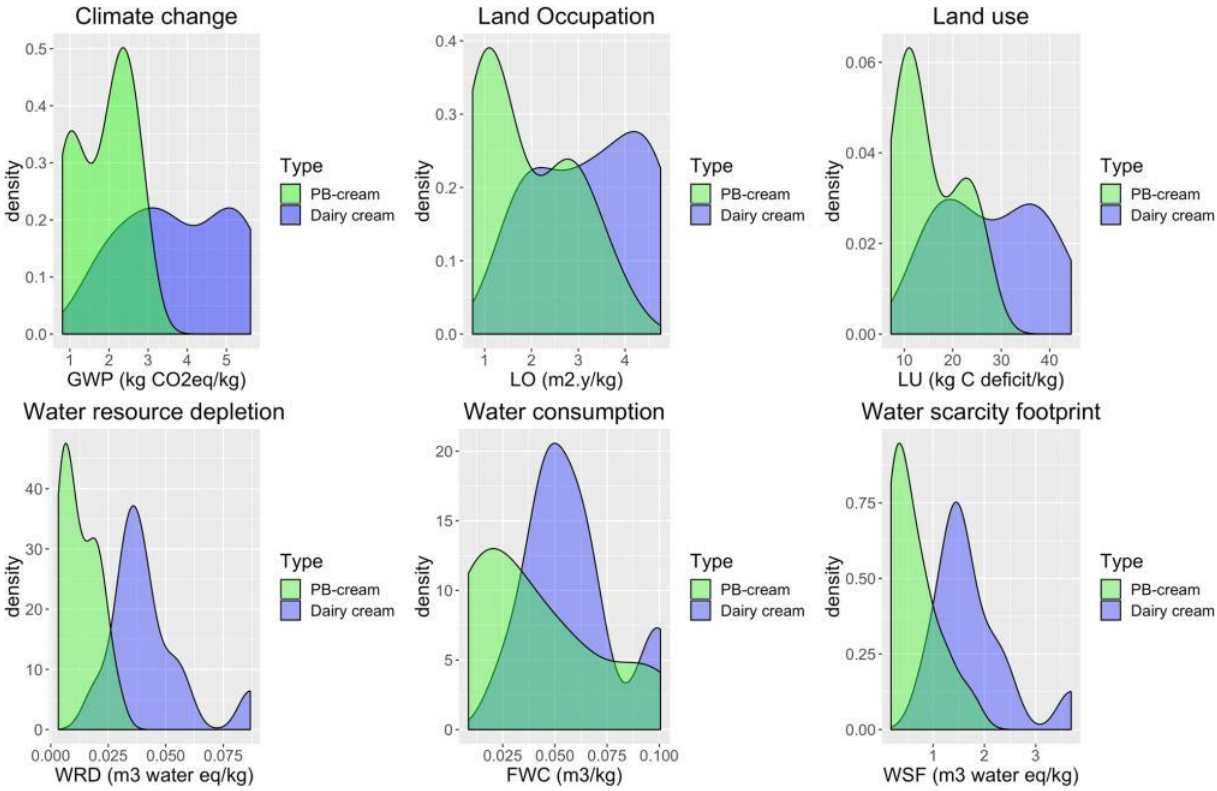

Figure 3.6 Comparison of environmental impacts between plant-based creams and dairy creams in all 21 markets

3.3.3 The influence of LUC on climate change

LUC influences climate change impacts for plant-based spreads and plant-based creams, due to the production of key ingredients such as palm oil, coconut oil or soybean oil. Figure 3.7 illustrates the contribution of LUC to climate change impacts of some ingredients included in the products. It shows that LUC alone can account for over 50% of climate change impacts of

many ingredients, with the most extreme case being soybean oil from Brazil with a contribution of 86%. Furthermore, the contribution of LUC also varies significantly among different ingredient-country combinations. Understanding spatial sourcing of ingredients is important. On average, for the dairy butter products assessed, they have a higher LUC impact on climate change than plant-based fat spread products.

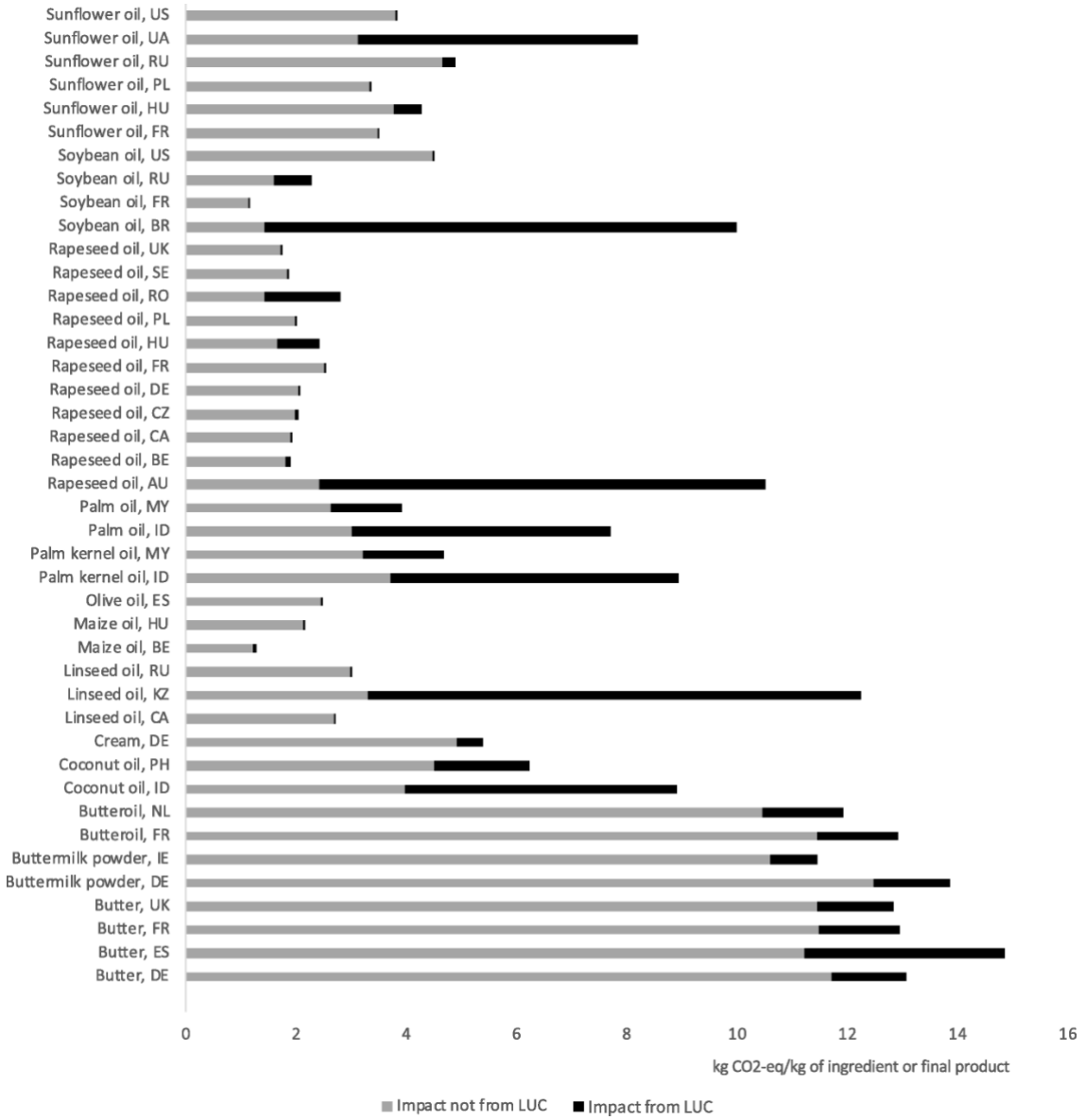

Figure 3.7 Contribution of LUC to climate impacts of selected ingredients and final products

3.3.3.1 The influence of allocation method choice for LUC

With LUC considered in the model for all crop production activities, the share of LUC highly depends on the allocation approach. Therefore, a sensitivity analysis was performed to evaluate the influence on total climate change impacts for different scenarios by choosing the “shared responsibility” rather than the “crop-specific” allocation approach. In the baseline assessment,

the "crop-specific" allocation approach was applied to allocate LUC to different crops within each producing country. In Figure 3.8, each point represents a different plant-based spread or plant-based cream scenario. Dots are displayed from highest to lowest LUC impacts calculated with the default "crop-specific" allocation approach. The crosses correspond to impacts calculated with the "shared responsibility" allocation approach. It shows that the default "crop-specific" approach, compared with the "shared responsibility" approach, generally allocates more LUC to the crops used in the plant-based spreads and plant-based creams (thus higher climate change impacts), with only a few exceptions. For all plant-based spreads and plant-based creams, the alternate allocation approach resulted in a 36% decrease to a 4% increase in total climate change impacts, with an average decrease of 12%, because crop-specific burden allocation approach attributes more GHG emissions to vegetable oilseeds ingredients included in this assessment. Overall, it shows the choice of crop-specific allocation approach as default is a more conservative allocation approach. For both allocation approaches, with respect to the comparative impacts of plant-based products and dairy butter and cream, climate change impacts remain stable.

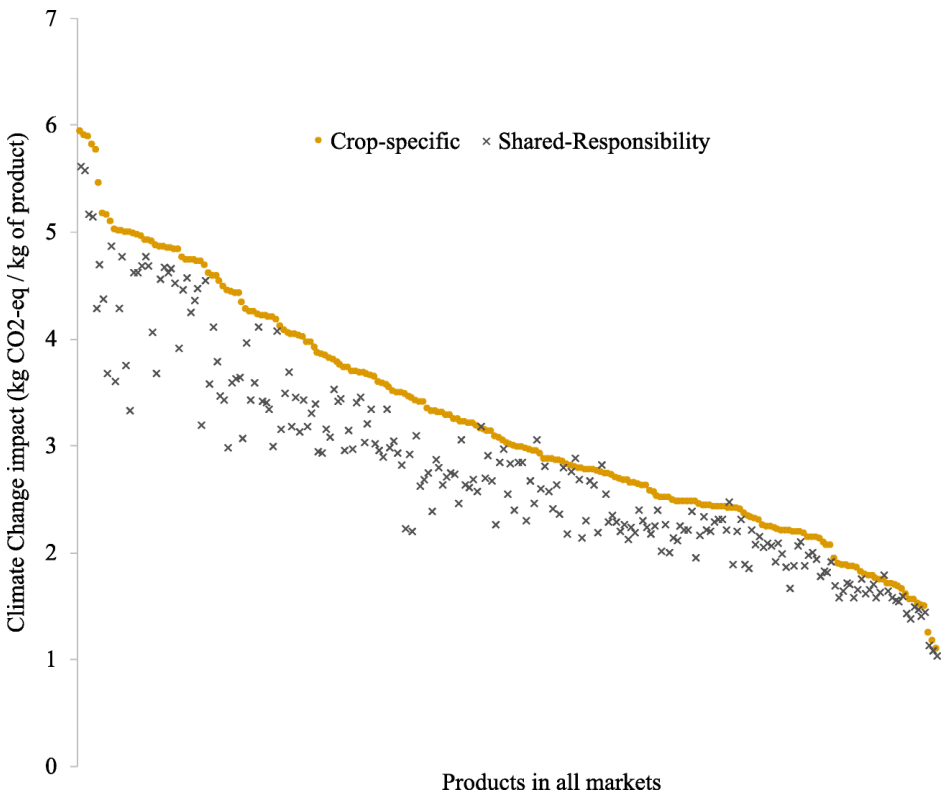

Figure 3.8 Climate change impacts of different LUC allocation approaches

(Each point represents a different plant-based spread or plant-based cream scenario. Dots are displayed from highest to lowest LUC impacts calculated with the default crop-specific allocation approach. The crosses correspond to impacts calculated with the shared responsibility allocation approach)

3.3.3.2 The worst-case sourcing scenario comparison for vegetable oils supply chain

Since vegetable oils are sourced worldwide and are traded as commodities, the countries of origin are generally known but the exact share from each country is unknown. Further, these proportions may vary from year to year. The LCA model assessed this data gap by considering import and production volume based on average historical FAOSTAT data, for each country where a factory producing the studied products is located. This sensitivity analysis aimed at generating a virtual "worst-case" scenario by considering sourcing countries with the highest climate change impacts for the main vegetable oils used in the plant-based spreads and plant-based creams. The following assumptions were made: 100% of palm oil and palm kernel oil sourced from Indonesia, 100% of sunflower oil sourced from Ukraine, 100% of rapeseed oil sourced from Australia, 100% of soybean oil sourced from Brazil and 100% of linseed oil sourced from Kazakhstan. A virtual "best case" scenario was considered for butter and dairy cream, where no LUC took place in the feed supply chain, giving a fair representation of non-fodder feed ingredients being sourced locally. The results from this sensitivity analysis demonstrates that even if plant-based spreads used vegetable oils with the highest climate change impacts (generally due to LUC in sourcing countries), total climate change impacts remained lower than dairy butter for 204 of the 212 plant-based products analyzed in 19 respective consumer markets. For 8 of the 212 products in Finland and Sweden, this "worst-case supply chain" scenario leads to climate change impacts that were 1% to 39% higher compared with "LUC free" butter. We found that the dairy systems in these two countries have much lower climate impacts compared with other countries and the LUC induced climate impacts for these plant-based spreads were found to be quite high, highlighting the importance of quantifying regional supply chain information of ingredient sourcing as well as associated spatially differentiated LUC impact.

3.3.4 Further sensitivity analysis

In this study, we performed further sensitivity analyses regarding functional unit choice, vegetable oils extraction allocation approach, packaging types and electricity production mix. Detailed discussions and results for each sensitivity analysis are available in the Annex. A summary of key insights obtained are discussed below.

- **Function unit choice**

The general trend for the LCA results was similar when considering a FU based on mass or volume. We also investigated the influence of considering a FU based on the total fat content, rather than on the total fresh mass, because most plant-based spreads generally have a lower fat content than butter, and a higher fact content often leads to higher climate, water and land impacts, vice versa (see more details in the Annex Fig. S1). Such consideration seems of low relevance when products are used for spreading based on volume, but could be pertinent when used in baking if, for instance, the percentage of fat used in a cake recipe influences the quality of the cake in terms of taste/performance. The total fat in a plant-based spread ranges from 300–800 g/kg, allowing consumers to choose the spread that best suits the required function e.g., spreading or baking. Plant-based creams often have a lower fat content than dairy cream, some even with a particularly low-fat content of < 100 g/kg. Butter typically has a total fat content of 800 g/kg and dairy creams in the present study had a total fat content ranging from 150 to 400 g/kg. For plant-based spreads, when changing the FU, the original conclusion still holds for climate change; similar patterns hold for water and land impact categories. As with the mass-based FU, there are significant overlaps between plant-based creams and dairy creams, and between dairy spreads and butter. With a fat-based FU, the overlaps are more pronounced.

- **Allocation method for vegetable oil extraction**

A sensitivity analysis was performed considering mass allocation in the vegetable oil extraction processes rather than the default economic allocation. Mass allocation generally attributes a lower share of the upstream burden to crude oil compared with economic allocation. The only exception is maize oil with a mass allocation factor of 19.6% and an economic allocation factor of 18.0% for the crude oil. The analysis showed that the total impacts of plant-based spreads and plant-based creams when mass allocation was applied was systematically lower than calculated for the baseline scenario, showing that the application of economic allocation for oil extraction and processing is rather conservative and is not likely to change the conclusions of the study.

3.3.5 Uncertainty analysis of climate change results

The robustness of climate change results is evaluated through an uncertainty assessment as described in Section 3.2.6. As shown in Figure 3.9, the uncertainty analysis shows that the higher bound of all 212 spreads, ranging from 0.98 to 6.93 (mean 3.3) kg CO2-eq, still have lower climate change impacts compared with the lower bound of all 21 butter products, ranging from

8.08 to 16.93 (mean 12.1) kg CO_2-eq with 95th confidence interval. However, the overlap of climate change results between plant-based spreads/creams and dairy spreads/creams increased.

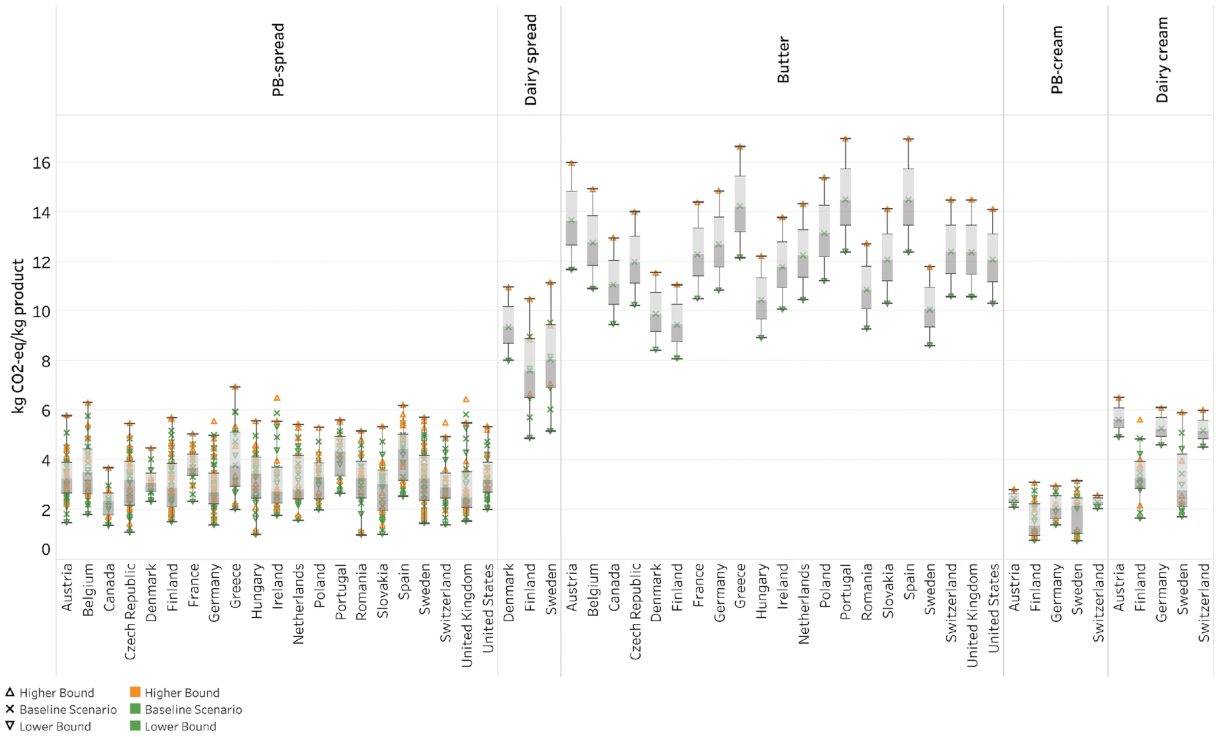

Figure 3.9 Uncertainty analysis of climate change impacts

3.4 Conclusions and outlook

The regionalized LCA conducted in this study is the largest scale regionalized agricultural LCA analysis comparing dairy butter and plant-based spreads published to date. It shows that plant-based spreads have lower climate, water and land impacts than butter, despite variability in product recipes and geographies and influence of LUC emissions. For climate change, the analysis shows all plant-based spreads perform better than butter regardless of the choice of functional unit (mass-based or fat-based), inclusion of LUC or allocation approach of oilseeds. It also shows that LUC of oilseed ingredients could dominate climate impacts for plant-based spreads; further, the hypothetical worst-case sourcing scenario (i.e., with the worst combination of oilseed type and sourcing country) performs worse than butter for climate impact, due to LUC associated with growing oilseed ingredients. Thus, inclusion of spatial LUC emissions is important for robust assessment and hotspot identification when taking steps towards mitigating the climate impact of food products. With respect to land occupation and water scarcity footprint, most plant-based spreads had lower impacts compared with butter in their respective consumer markets, with only a few exceptions (8 of 212 products) which contained oilseed

ingredients with high embodied impacts, caused by growing in high water-stressed regions with either low yield or high water demand.

Towards transparency of sustainable supply chains and developing potential mitigation strategies, producers can only understand the impacts of their products and look for opportunities to reduce these impacts if they fully and accurately assess their product supply chains. The regionalized LCA results highlight significant interindividual variabilities on the product level for plant-based spreads, driven by differences in product recipe designs and spatial variabilities of sourcing ingredients.

The framework introduced and demonstrated in this study offers opportunities for hotspot identification as well as insights for improving the sustainability of a large portfolio of products. For example, towards more sustainable plant-based spreads, the key solution would be to reduce embodied environmental impacts from oilseed ingredients through better understanding and improvements in supply chain sourcing, farm level agricultural practice and product recipe design. The key challenges of performing large-scale regionalized LCA lies in the collection and organization of all relevant data and models, performing gap assessment and prioritization, developing missing data or improving data quality and linking inventory data with impact assessment, to draw robust conclusions and meet requirements for data quality.

The application of the methodology framework in this study demonstrated the feasibility of conducting large-scale regionalized LCA for agri-food products. This principle is also relevant for other product type evaluations and this study offers step-wise guidance. We believe it will contribute to the operationalization of regionalized LCA in practice towards identifying inter-product variabilities as well as highlighting hotspots for improving transparency and sustainability of product supply chains.

When moving towards developing more tangible mitigation strategies on a finer spatial scale, such as field or farm level intervention, it is important to verify the findings obtained from a high-level spatial scale and interpret the variabilities and hotspots identified by the country-scale regionalized LCA. This requires further improving (1) transparency and accuracy of supply chain sourcing information of key ingredients, (2) gathering, modeling and understanding agricultural information at a finer scale for parameters such as soil health and fertility characteristics, climate factors, crop yield, fertilizing and irrigation situations etc., through techniques, such as field sensors, surveys or remote sensing data, as well as potential

predictive analysis of future scenarios coupling with geographical information system (GIS) features; (3) a more robust modeling and understanding of spatial-sensitive environmental mechanisms and the links between activity data and impact assessment.

Contributions Xun Liao conceived the methodology framework in this paper and overall modeling architecture, building the supply chain modeling and system modeling tool, performing analysis, data visualization, interpretation, and main writing of the manuscript. Monique Gerichhausen contributed to the writing of the manuscript. Xavier Bengoa contributed to the discussion of defining the overall modeling architecture, the spatial agricultural LCI dataset development, gap assessment and analysis, and provided inputs for the writing. Giles Rigarlsford contributed to giving valuable inputs and improving the writing of the manuscripts. Ralph Beverloo and Yvonne Bruggeman contributed to primary data collection. Vincent Rossi contributed to the dairy system modeling and updated LUC modeling.

3.5 Reference

Blonk Agri-footprint BV(2015) Agri-footprint - Part 2 - Description of data. Gouda, the Netherland

Blonk Consultants (2013) Direct Land Use Change Assessment Tool Version 2013.1. http://www.blonkconsultants.nl/direct-land-use-change-assessment-tool/?lang=en

Boulay A-M et al (2017) The WULCA consensus characterization model for water scarcity footprints: assessing impacts of water consumption based on available water remaining (AWARE). Int J Life Cycle Assess. https://doi.org/10.1007/s11367-017-1333-8

BSI (2012) PAS 2050-1:2012 Assessment of life cycle greenhouse gas emissions from horticultural products. British Standard Institute. London, the United Kingdom

Cederberg C, Stadig M (2003) System expansion and allocation in life cycle assessment of milk and beef production. Int J Life Cycle Assess 8:350–356.

De Schryver A, Galatola M, Kerkhof A-M (2016) Guidance for modeling transport from factory to client in PEFCRs. Issue paper, v0.1, June 2016. European Commission DG-Environment. Brussels, Belgium

EDA (2016) Product Environmental Footprint Category Rules for Dairy Products. Draft report (28 July 2016). The European Dairy Association. Brussels, Belgium

Ekvall T, Weidema B (2004) System Boundaries and Input Data in Consequential Life Cycle Inventory Analysis. Int J Life Cycle Assess. 9(3) 161-171

European Commission, PEFCR Guidance document, - Guidance for the development of Product Environmental Footprint Category Rules (PEFCRs), version 6.3, December 15 2017.

FAOSTAT (2006-2011) Vegetable oil production and import volumes. http://faostat.fao.org/. Accessed November 2016

FEFAC (2016) Product Environmental Footprint Category Rules for Feed for Food Producing Animals. Draft report v1.5 (22 July 2016). The European Feed Manufacturers' Federation. Brussels, Belgium

Ference et al (2017) Low-density lipoproteins cause atherosclerotic cardiovascular disease. 1. Evidence from genetic, epidemiologic, and clinical studies. A consensus statement from the European
Atherosclerosis Society Consensus Panel. Eur Heart J 21;38(32):2459-2472

Godfray HC, Beddington JR, Crute IR, Haddad L, Lawrence D, Muir JF, Pretty J, Robinson S, Thomas SM, Toulmin C (2010) Food security: the challenge of feeding 9 billion people. Science 327(5967):812-818

Goedkoop M, Heijungs R, Huijbregts MAJ, Schryver A, De Struijs J, van Zelm R (2013) ReCiPe 2008: A life cycle impact assessment method which comprises harmonised category

indicators at the midpoint and endpoint level. First edition (version 1.08). Report I: Characterisation

Gonzalez Fischer C, Garnett T (2016) Plates, pyramids, planet. FAO and the Environmental Change Institute & The Oxford Martin Programme on the Future of Food, The University of Oxford

Grünberg J, Nieberg H, Schmidt T (2010) Treibhausgasbilanzierung von lebensmitteln (carbon footprints): Überblick und kritische reflection. Landbauforschung - vTI Agriculture and Forestry Research 2(60): 53-72

Hellweg S, Milà i Canals L (2014) Emerging approaches, challenges and opportunities in life cycle assessment. Science 344:1109–1113.

Humbert S, Guignard C (2015) PEF / OEF: Default data to be used to model distribution and storage. Issue paper, v2.1, December 2016. European Commission DG-Environment. Brussels, Belgium

IDF (2015) A common carbon footprint approach for Dairy. The IDF guide to standard life cycle assessment methodology for the dairy sector. International Dairy Federation. Brussels, Belgium

IPCC (2006) IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, forestry and other land use. IGES, Kanagawa, Japan.

ISO (2006a) Environmental management – life cycle assessment – principles and framework, ISO 14040:2006(E). International Organization for Standardization, Geneva

ISO (2006b) Environmental management – life cycle assessment – requirements and guidelines, ISO 14044:2006(E). International Organization for Standardization, Geneva

JRC-IES (2011). International Reference Life Cycle Data System (ILCD) Handbook-Recommendations for Life Cycle Impact Assessment in the European context. First edition November 2011. European Commission-Joint Research Centre - Institute for Environment and Sustainability. Publications Office of the European Union, Luxemburg

Kling MM, Hough I (2010) The American carbon foodprint: understanding your food's impact on climate change. White paper. Middlebury, VT: Brighter Planet, Inc. http://www.kohalacenter.org/HISGN/pdf/carbofoodprint.pdf

Kramer GFH, Tyszler M, Veer P v, Blonk H (2017) Decreasing the overall environmental impact of the Dutch diet: how to find healthy and sustainable diets with limited changes. Public Health Nutrition, 1-11. https://doi.org/10.1017/S1368980017000349

LEAP (2015) Environmental performance of animal feeds supply chains: Guidelines for assessment. Livestock Environmental Assessment and Performance Partnership. The Food and Agriculture Organization of the United Nations (FAO), Rome, Italy

Masset G, Soler L-G, Vieux F et al (2014) Identifying sustainable foods: the relationship between environmental impact, nutritional quality, and prices of foods representative of the French diet. J Acad Nutr Diet 114, 862–869

Mensink RP (2016) Effects of saturated fatty acids on serum lipids and lipoproteins: a systematic review and regression analysis. Geneva: World Health Organization

Milà i Canals L, Rigarlsford G, Sim S (2012) Land use impact assessment of margarine. Int J Life Cycle Assess 18(6), 1265–1277. https://doi.org/10.1007/s11367-012-0380-4

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

Nemecek T, Gaillard G, Freiermuth R, Antón A, Wilfart-Monziols A, Hermansen J (2011) ecoinvent V3.0 - Good practice for life cycle inventories in agriculture (plant and animal production). Version: 1.4 – June 2011. Agroscope Reckenholz-Taenikon Research Station ART, Swiss Centre for Life Cycle Inventories, Zurich and Dübendorf, Switzerland

Nemecek T, Schnetzer J, Reinhard J (2014) Updated and harmonised greenhouse gas emissions for crop inventories. Int J Life Cycle Assess 21(9):1361–1378

Nemecek T, Bengoa X, Lansche J, Mouron P, Rossi V, Humbert S (2015) Methodological Guidelines for the Life Cycle Inventory of Agricultural Products. Version 3.0. World Food LCA Database. Quantis and Agroscope. http://www.quantis-intl.com/wfldb/files/WFLDB_MethodologicalGuidelines_v3.0.pdf.

Nilsson K, Flysjö, Davis J, Sim S, Unger N, Bell S (2010) Int J Life Cycle Assess 15:916-926

O'Brien D, Capper JL, Garnsworthy PC, et al (2014) A case study of the carbon footprint of milk from high-performing confinement and grass-based dairy farms. J Dairy Sci 97:1835–1851. doi: 10.3168/jds.2013-7174

Quantis 2016. ALCIG - Agricultural Life Cycle Inventory Generator. https://alcig.quantis-software.com/

Scarborough P, Appleby PN, Mizdrak A, Briggs AD, Travis RC, Bradbury KE, Key TJ (2014) Dietary greenhouse gas emissions of meat-eaters, fish-eaters, vegetarians and vegans in the UK. Climatic change 125(2): 179-192

Schau EM, Palomino J-A, Michalopoulos G, Russo C (2016) Product Environmental Footprint Category Rules for Olive Oil – 3rd Draft. Draft version 0.5

Scientific Report of the 2015 Dietary Guidelines Advisory Committee. Washington, DC: US Departments of Agriculture and Health and Human Services, 2015

Soret S, Mejia A, Batech M et al (2014) Climate change mitigation and health effects of varied dietary patterns in real-life settings throughout North America. Am J Clin Nutr 100, Suppl. 1, 490S–495S

Thoma G, Popp J, Nutter D, et al (2013) Greenhouse gas emissions from milk production and consumption in the United States: A cradle-to-grave life cycle assessment circa 2008. Int Dairy J 31:S3–S14. doi: 10.1016/j.idairyj.2012.08.013

UNEP (2016) Global guidance for life cycle impact assessment indicators. Volume 1. ISBN: 978-92-807-3630-4. Available at: http://www.lifecycleinitiative.org/life-cycle-impact-assessment-indicators-and-characterization-factors/

UN Food and Agriculture Organization (2010) Greenhouse Gas Emissions from the Dairy Sector. A Life Cycle Assessment

Vieux F, Darmon N, Touazi D, Soler LG (2012) Greenhouse gas emissions of self-selected individual diets in France: Changing the diet structure or consuming less? Ecological Economics 75:91-101

Vermeulen, S. J., Campbell, B. M. & Ingram, J. S. I. Climate Change and Food Systems. Annu. Rev. Environ. Resour. 37, 195–222 (2012).

Weidema BP, Bauer C, Hischier R, Mutel C, Nemecek T, Reinhard J, Vadenbo CO, Wernet G (2013). Overview and methodology. Data quality guideline for the ecoinvent database version 3. Ecoinvent Report 1(v3). The ecoinvent Centre. St. Gallen, Switzerland

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(9):1218–1230

Wickham H, Chang W, Henry L, et al (2018) ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics

Willett W, Rockström J, Loken B, et al (2019) Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. The Lancet. doi: 10.1016/S0140-6736(18)31788-4

Xue B, Yan T, Ferris CF, Mayne CS (2011) Milk production and energy efficiency of Holstein and Jersey-Holstein crossbred dairy cows offered diets containing grass silage. J Dairy sci. 94(3):1455-1464

4 The carbon footprint of the Power-to-Gas

4.1 Introduction

To limit the increase in global temperature under 1.5 °C, the development of low-carbon technologies for energy transition becomes strategically crucial for all societies (IPCC 2018). Variable renewable energy sources (VRE), such as wind and solar, have the technical potentials to supply the global energy demand(Jacobson and Delucchi 2011). However, the VRE and its availability are unevenly distributed across different periods and regions, resulting in the imbalance of supply and demand across different time scales (daily and seasonal periods) and grid instability. Incorporating energy storage technologies along with VRE deployment towards energy transition is thus indispensable for achieving high penetration of renewable electricity. The German energy transition experience shows that the focus of decarbonization of electrical grids alone is not sufficient for meeting the decarbonization target if not connecting the renewable power sector with industry, transport, and heat/cooling demand, termed as "sector coupling" (Brown et al. 2016; Blanco and Faaij 2018). Among existing energy storage technologies (Luo et al. 2015), Power-to-Gas (PtG) is viewed as more suitable for large scale long-term seasonal storage of electric power (Moore and Shabani 2016; Blanco and Faaij 2018) and is the key enabler for sector coupling (Michalski et al. 2017; Buttler and Spliethoff 2018; Robinius et al. 2017). Various national incentive schemes are introduced to financially support clean fuel development in Europe based on sustainability criteria requiring, at minimum, the reduction of carbon footprint, measured as CO_2-equivalent of different greenhouse gases (GHGs) emissions using global warming potential (GWP) metric with the life cycle assessment (LCA) approach (Koponen and Hannula 2017; Meylan et al. 2017; Spielmann et al. 2015; Kreeft 2018). Although LCA of Power-To-X concept was reviewed by Koj et al. (2019), however, it does not focus on addressing the validity of applying LCA of PtG to support carbon footprint reduction claim. Building on the review from Koj et al. (2019), we expanded the literature review of the LCA of PtG through the Google scholar search for the period of 2011-2020. The search criteria include "LCA or life cycle assessment", and "power to gas or PtG or power to methane". A total of 32 published articles and research reports are identified, with detailed results provided in Table 4.1 and Table 4.2. It covers the product (H_2, CH_4) assessed, regulatory target for GHGs reduction, spatiotemporal coverage, allocation approaches, foreground data, technologies for electrolysis and methanation, CO_2 sourcing, electricity type and modeling choices as well as threshold value of electricity carbon intensity to have a lower carbon footprint than fossil counterparts. Through the literature review, we identified two key pitfalls that hinder the validity of evaluating the carbon footprint of PtG, elaborated as follows:

- **The allocation and accounting problem related to CO_2 feedstock**. Various studies show the LCA results of PtG production are sensitive to the choice of allocation method (Sternberg and Bardow 2015; Zhang et al. 2017; Parra et al. 2017; Koj et al. 2019). From the review, not all LCA studies specify what allocation methods are used. Furthermore, there are different interpretations of the allocation rule from the ISO 14044 standard, resulting into inconsistent applications of allocation procedures related to CO_2 feedstock. Notably, when CO_2 is sourced from fossil origins, 100% of the climate burden of the emission of the molecular carbon from the CO_2 feedstock is allocated to the PtG production systems with an allocation at the point of substitution in Blanco et al. (2020) and with a sub-division approach in Zhang et al. (2020). However, Muller (2020) argues it is not required to distinguish sources that supply biogenic, fossil, or CO_2 captured from ambient air when calculating the carbon footprint of CO_2 feedstock, following the recommended substitution approach. Reiter and Lindorfer (2015) differentiate the biogenic and fossil origin of the sourcing CO_2 and argues CO_2 feedstock from a biogenic source can be treated as "carbon neutral" if there is no climate impact from separation in a "cradle to gate" analysis. Muller et al. (2020) argues, for all CO_2 sources, the cradle-to-gate footprint of captured CO_2 is negative ranging from −0.95 to −0.59 kg CO2 eq. per kg of feedstock CO_2 today.
- **Grid emission modeling choices and spatiotemporal variabilities.** Although the GHG intensity of electricity is the crucial factor for the carbon footprint of PtG (Spielmann et al. 2015; Koj et al. 2019), discussions are mainly related to its generation types (renewable or country-specific mix), but almost none of the studies discuss the influence of methodological choices (Sotos 2015; Brander et al. 2018; Soimakallio et al. 2011; Qu et al. 2017a) and temporal variabilities (Vuarnoz and Jusselme 2018; Messagie et al. 2014) related to electricity modeling when assessing the carbon footprint of PtG technologies. For example, should it be based on the location-based approaches (territory production-based vs consumption-based perspective), or the market-based approach, differentiating GHG emissions for different users based on the contractual relationship, such as the guarantees of origins (GOO) (Association of Issuing Bodies 2019)? Would the choice of different temporal resolution of electricity GHG emissions have a large influence for calculating the carbon footprint of PtG?

Table 4.1 Scope of the Power-to-Gas LCA studies

Author	Product		Scope				Foreground		Electrolysis			Methanation		CO_2 sources			
	H_2	CH_4	Regulatory target	Spatial	Temporal	Allocation[6]	Primary[4]	Inf.[5]	AEL	PEM	SOEC	Thermal chemical	biological	Biogas	DAC	WWTP	Others
Trost 2011	x	x		DE	annual	x			x			x		x			
Jentsch 2014	x	x		DE	annual		x	x		x		x		x			
Steinmüller 2014	x	x		AT	annual	x			x	x		x		x			
Spielmann 2015	x	x	x[1]	CH	annual			x	x			x			x		x
Sternberg 2015	x	x		DE	annual	x						x					x
Reiter 2015	x	x		EU	annual												
Sternberg 2015	x	x		multiple	annual					x		x					x
Jess 2016	x	x		DE	annual	x	x	x			x	x			x		x
Sternberg 2016	x	x		DE	annual	x		x		x		x					x
Hoppe 2016	x	x		DE	annual					x		x		x			x
Parra 2017	x	x		CH, EU	annual	x		x		x		x		x	x		
Koponen 2017	x	x	x[2]	FI,Nordic	annual	x				x	x	x					x
KIT 2017	x	x		DE	annual	x	x				x	n.s	n.s	x	x		x
Zhang 2017	x	x		CH, EU	annual	x	x		x	x		x		x	x		x
Uusitalo 2017	x	x		EU	annual	x				x		x					x
Meylan 2017	x	x	x[3]	EU	annual	n.s.			n.s	n.s	n.s	n.s	n.s	x	x		x
Electrochaea 2017	x	x		DK	annual	n.s	x	x		x			x			x	
Wettstein 2017	x	x		CH	annual			x	x			x	x		x		x
Collet 2017	x	x		FR	annual	x			x			x		x			
Vo 2017	x	x		IE	annual	x			n.s	n.s	n.s		x	x			
Vo 2018	x	x		IE	annual	x				x			x	x			
Castellani 2018	x	x		IT	annual	x			n.s	n.s	n.s	x		x			
Deutz 2018	x	x		EU	annual	x		x		x		x		x	x		
Tschiggerl 2018	x	x		AT	annual				x			x					
Castellani 2018	x	x		IT	annual	x				x		x					x
Hoppe 2018	x	x		DE	annual					x		x		x	x		x
Wettstein 2018	x	x		CH	annual			x	x			x	x		x		x
Koj 2018	x	x		DE	annual	x			x			x		x			
Blanco 2020	x	x		EU	annual, seasonal	x		x	x			n.s	n.s	n.s	n.s	n.s	n.s
Zhang 2020	x	x		CH	annual	x		x		x		x		x			
Sadok 2020	x	x		Multiple	annual	n.s		x			x	x					x

Abbreviations: n.s=not specified; n.a=not available; blank= no information; x= exist

[1] Mineral tax exemption in Switzerland measured by LCA: 40% less GWP, no more than 125% total impact results (UBP)

[2] RED thresholds: 70% reduction

[3] EU Directive 2015/652

[4] Primary data refer to the firsthand data usually collected from a demonstration plant

[5]Infrastructure (mainly) related to methanation plants

[6] Most allocation is related to CO_2 input, lesser with (surplus) electricity input, but also related to multi-product output, such as handling of O_2, excess heat, or other by-product.

Table 4.2 Type of electricity sources, modeling choices and threshold values in PtG LCA studies

Author	Surplus	PV	Wind	Hydro	National grid	EU mix	Temporal resolution	Threshold H_2 (CO_2-eq/kWh)	Threshold CH_4 (CO_2-eq/kWh)
Trost 2011	x				x		Annual		
Jentsch 2014	x		x		x		Annual		
Steinmüller 2014		x	x		x		Annual		
Spielmann 2015[2]	x		x		x		Annual		
Sternberg 2015	x						Annual		
Reiter 2015		x	x			x	Annual	190	73-113
Sternberg 2015	x						Annual		
Jess 2016		x	x		x		Annual		
Sternberg 2016	x				x		Annual		82
Hoppe 2016		x					Annual		
Parra 2017		x	x		x		Annual		
Koponen 2017			x		x	x	Average		84–110
KIT 2017			x		x		Annual		
Zhang 2017		x	x		x	x	Annual		
Uusitalo 2017	x	x					Annual		
Meylan 2017	x	x	x	x			Annual		
Electrochaea 2017			x		x		Annual		
Wettstein 2017	x		x		x		Annual		
Collet 2017					x	x	Annual		
Vo 2017	x		x				Annual		
Vo 2018					x		Annual		
Castellani 2018		x			x		Annual		
Deutz 2018			x		x	x	Annual		
Tschiggerl 2018		x	x		x	x	Annual		
Castellani 2018		x			x		Annual		
Hoppe 2018		x					Annual		
Wettstein 2018	x		x		x		Annual		
Koj 2018	x						Annual		
Blanco 2020		x	x		x		Annual, Seasonal		123–181; 4–62
Zhang 2020		x					Annual		152-336
Sadok 2020		x	x		x		Annual		

Abbreviations: n.s=not specified; n.a=not available; blank= no information; x= exist

All studies didn't discuss the difference between production vs consumption-based carbon footprint accounting related to electricity, except Spielmann et al. (2015). There is also no discussion related to the modeling of electricity input with GOO (Guarantee of origins) and residual mix.

In this paper, we aim to provide a systematic methodological framework for assessing the carbon footprint of PtG based on the regionalized LCA approach to address the pitfalls mentioned above, illustrated with three case studies. Section 4.2 gives the definition of PtG and the description of the three actual demonstration plants, representative of different combinations of technology choices, CO_2 sourcing and system variations under different regional characteristics. Section 4.3 describes a systematic LCA methodological framework for calculating the carbon footprint of PtG that addresses the allocation problems of CO_2 feedstock and different electricity GHG emission modeling approaches. Section 4.4 discusses the application of the methods for addressing the pitfalls illustrated with the three case studies. Finally, we draw the conclusion and recommendations towards a more robust assessment of the carbon footprint of PtG.

4.2 Definition and description of the PtG demonstration plants

Following the definition proposed in the project STORE and GO (2020), in this study, PtG is defined as "the use of electrical energy to produce hydrogen in an electrolyzer (Power to hydrogen, PtH) and synthesizes this hydrogen with carbon dioxide to methane (Power to methane, PtM)". The PtG technology is currently mainly available in pilot and demonstration projects (Gahleitner 2013; Bailera et al. 2017). The techno-economic background of PtG is given in various studies (Blanco and Faaij 2018; Götz et al. 2016; Varone and Ferrari 2015; Schemme et al. 2017; Albrecht et al. 2017; McKenna et al. 2018; Ghaib and Ben-Fares 2018), regarding the types and efficiencies of different electrolysis and methanation technologies and the rationale of further converting hydrogen into methane or synthetic natural gas (SNG). Figure 4.1 shows the general description of the three PtG demonstration plants in Europe developed within the EU H2020 Framework Store&Go project (2020) that will be used in this study to validate our framework. These PtG demonstration plants are designed to representatively consider different combinations of technology choices and system configurations under various regional characteristics, including i) different types and availability of renewable electricity generation technologies and CO_2 sourcing options in different European locations; ii) different electrolyzer technologies; iii) three different innovative methanation processes at a considerable scale varying between 200 kW and 1 MW located in three different demonstration environments with varying heat valorization opportunities. Primary raw data from the demonstration sites are collected from plant owners and project partners. A summary of critical parameters is given in Table 4.3. The subsections

below give a brief overview of characteristics of CO_2 capture and supply, efficiency of electrolyzes, methanation and process heat integration and valorization.

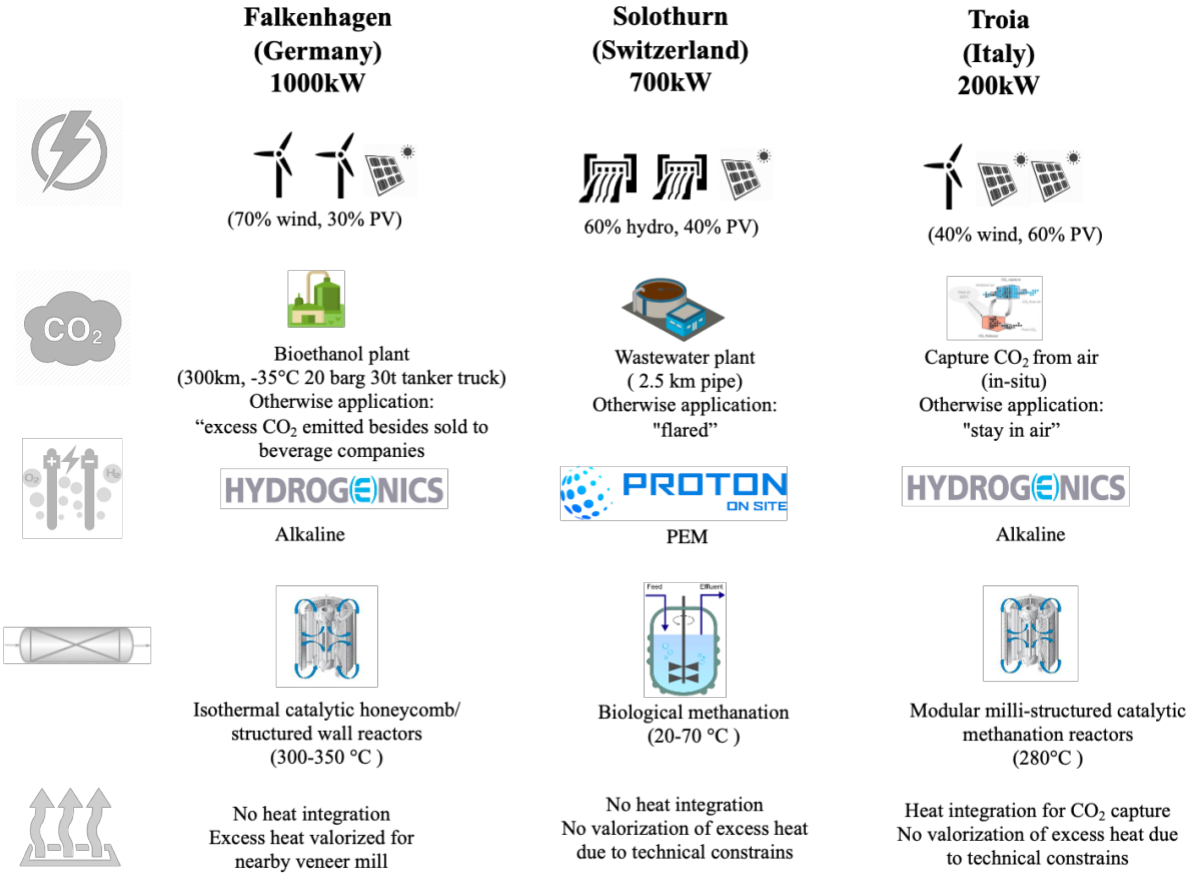

Figure 4.1 General characteristics of the three representative PtG demonstration plants

Table 4.3 Key utility, material and yield of main product and co-product

Stages	Item	Unit	Falkenhagen	Solothurn	Troia
PtH					
Electrolysis	Electrolyzer type	-	HySTAT-60-10 (AEL)	Proton onsite C30 (PEM)	HySTAT-60-10 (AEL)
	Electricity input	kWh	1000	700	200
	Efficiency (AC power) [9]	kWh/Nm^{3}H$_2$	4.77	5.83	4.93
	H_2O input	kg/h	315-420 (RO)[2]	108 (deionized)	61-81 (RO)
	H_2 output	kg/h	18.74	10.71	3.6
		m^3/h	209.87	120	40.56
		MJ (HHV)	2661	1521	511
		MJ (LHV)	2249	1285	432
	Deliver pressure	Bar	10	30	10
	H_2 storage	m^3(NTP) @14 bar		292	
PtM (further methanation)					
CO_2 capture and supply		kWh	12.16[5]+ 7.8[6]	0.5 + 4[7]	30.8[8]
Methanation+others		kWh	187	26.54	8
	Methanation reactor	-	Honeycomb catalytic	Biological	Modular catalytic
Auxiliary input	Heating & cooling water	m^3/h	28	8.6	7.5
	Instrument air	m^3/h	45	25	8.33
	Nitrogen	kg/flush[3]	90	50	17
	Catalyst type	-	Ni	Biocatalyst	15-20% Ni/Al_2O_3
	Catalyst quantity	kg/reactor[4]	220	Buffer nutrients	8
	Heat delivery medium	-	Hot water/ Therminol oil	water	Water
	SNG output	m^3/h (NTP)	52.5	30	10.1
		kg/h	37.35	20.7	7.3
		MJ (HHV)	2321	1326	454
		MJ (LHV)	1878	1073	367
	SNG deliver pressure	bar	13	13	13
	Deliver pressure	Bar	13	13	13
	System efficiency(HHV)	%	53	50	53
	System efficiency (LHV)	%	43	41	43
	CH_4 concentration	mol-%	98.3	97.3	93.8
	H_2 concentration	mol-%	1.4	1.8	5
	CO_2 concentration	mol-%	0.4	0.9	1.2
Heat valorization	Heat integration	kW/h			16.5
	Surplus heat	kW/h	113	(100) [1]	(14.6) [1]
System parameters					
Default electricity type		-	70% wind, 30% PV	60% hydro, 40% PV	40% wind, 60% PV
Operating hours		Hours/year	4000	4000	4000
Lifetime	Electrolyzer life	Hours	80000	80000	80000
	Plant and other equipment life	Years	15	15	15

[1] Not valorized
[2] Reverse osmosis water
[3] three times of purse per year
[4] Life time = 4000 hours, conservative estimate (4000-8000 hours, per communication with Föcker/UST) In industry, regular catalyst lifetime is 3 years, thus 25,000 h hours could be possible
[5] CO_2 liquefaction energy. CO_2 from the fermentation process is pure, only a compression unit is necessary to condition.
[6] CO_2 transportation energy
[7] 0.5 kW for blowing the CO_2 through a pipeline, 4 kW for compression of CO_2 feeding system
[8] Capture energy from Climeworks. Partial heat provided by reactor heat recovery
[9] The variability reported in the literature is 50 – 65 kWh /kg H_2

4.2.1 CO_2 capture and delivery

CO_2 feedstock can be captured from various sources, such as from biogenic sources, direct air capture (DAC) or fossil/ industrial sources. In this study, we narrowly focus on CO_2 from bioethanol plant, wastewater plant and DAC for the three demonstration plants.

- Falkenhagen demonstration site: CO_2 from bioethanol plant

The CO_2 feedstock is produced by a sugar/bio-ethanol factory (100% biogenic origin). As the CO_2 stream from the fermentation step is assumed to be pure CO_2, no "capture unit" is required (Laude et al. 2011). If CO_2 is not utilized by the PtG plant in Falkenhagen, it is sold to beverage companies with excess emitted to the air. The captured pure CO_2 is first compressed into a liquid form. The liquid CO_2 is transported by tank truck with a 30t storage tank, -35°C 20 bar for the distance of 300 km.

- Solothurn demonstration site: CO_2 from a wastewater treatment plant

The CO_2 is separated by membranes from biogas, which is considered as a waste product of the wastewater treatment plant. There was an already existing system in the waste treatment plant for separating the CO_2 and CH_4. The CO_2 was either vented to the atmosphere or sent to an incineration plant for diluting their combustion gases. The CO_2 is delivered with a 2.5 km pipeline. The electric demand for blowing the CO_2 from the wastewater treatment plant to the methanation plant is 0.5 kW per hour as reported in Table 4.3.

- Troia demonstration site: CO_2 captured directly from the air

The CO_2 is captured *in-situ* with the direct air capture technology provided by Climeworks. Detailed energy and bill of materials related to the equipment are collected directly from Climeworks. The CO_2 production is a batch process with three reactors, which are cooperated for adsorption-desorption cycle for a continuous CO_2 flow. The energy requirement includes thermal energy demand 1500- 2000 kWh/t CO_2 at @100 °C and electricity demand 200-300 kWh/t CO_2. In the current system deployed in Troia, all energy demands are provided by electricity. The heat requirement is partially reduced by integrating heat recovered from the methanation reactor.

4.2.2 Electrolysis

Both the Alkaline and PEM electrolyzers are commercialized for hydrogen production and used in the demonstration plants. Alkaline electrolysis is a well-established technology with relatively low cost and long-term stability, whereas PEM has higher current densities, good partial load range, and rapid system responses. The key factors for LCA are electrolyzer energy

efficiency, stack lifetime, and capacity of production. The efficiency, measured as output hydrogen Energy (HHV) / input electrical energy, of a (PEM or alkaline) electrolyzer reported in the demonstration sites is currently around 60-73% (4.8 - 5.8 kWhel/Nm^3-H_2 in Table 4.1 or 53 - 65 kWhel/kg-H_2). In the future, the efficiency of an electrolyzer (2-phase system, liquid water @25 °C, 1 bar) could reach 80% (4.4 kWhel/Nm^3-H_2 or 50 kWhel/kg-H_2). Currently, the surplus heat produced from PEM and Alkaline electrolyzers is not utilized. The oxygen output is released directly into the air.

4.2.3 Methanation reactors

Three different methanation reactors are deployed: (i) catalytic honeycomb/structured wall methanation reactors in Fakenhagen; (ii) biological methanation in Solothurn (iii) modular milli-structured catalytic methanation reactors in Troia. The detailed characteristics are reported in Table 4.1.

4.2.4 Process heat integration and surplus heat valorization

Falkenhagen site can recover 113 kW of heat per hour from methanation reaction and send them back to the nearby veneer mill to replace the heat provided by natural-gas boiler by default and displace "heat hump" as sensitivity. For Solothurn, the surplus heat cannot be valorized. For Troia, it integrates 16.5 kW methanation reaction heat for the direct air capture of CO_2. The remaining heat is lost due to the lack of viable opportunities.

4.3 Methodology

The attributional LCA methodology is used to assess PtG production systems, following the ISO 14040 and ISO 14044 standards and the recommendations given in the FC-Hy guide for performing LCAs on hydrogen technologies (Masoni and Zamagni 2011).

4.3.1 Function and Functional unit, and referent product

The function of the studied systems is to generating and combusting hydrogen or SNG through PtG technologies. Two functional units and reference flows are defined as follows:

- PtH: 1 MJ of H_2, 10-30 bar, gas phase, after oxidation.
- PtM: 1 MJ of SNG, 13 bar, 96% purity, after oxidation.

The carbon footprint of the three assessed PtG demonstration plant are benchmarked to the following reference products. For the PtH, the reference product is H_2 produced from steam reforming of natural gas with the default GHG intensity of 14.08 kg CO_2-eq / kg H_2 or 116.73 g CO_2-eq/MJ of H_2 considered (range: 10.92-15.96 kg CO_2-eq/ kg-H_2) (see Table A1 in

Appendix). For the SNG production from the PtM, the fossil natural gas mix (global average, "Natural gas, high pressure {GLO}| market group for | Cut-off") from the ecoinvent v3.5 (2020) is used by default with a GHG intensity of 0.38 kg CO_2-eq for producing 1 Nm^3 of natural gas (LHV=36.4 MJ/Nm_3) or 10.44 g CO_2-eq /MJ for producing 1 MJ of natural gas. The chosen value is close to the median value of the 29 country or regions reported in the ecoinvent database with a range of 0.11-0.97 kg CO_2-eq/Nm_3-natural gas, and it also closely represents the average European natural gas. The combustion emission of natural gas is 1.94 kg CO_2-eq/Nm_3 or 53.26 g CO_2-eq/MJ. Although two separate function units are defined in this study, our focus of analysis is on PtM.

4.3.2 System boundary and allocation

The scope of this LCA study is cradle to grave. Figure 4.2 illustrates the system boundaries for the PtG production systems following the nomenclature recommended by the EC-JRC ILCD Handbook (EU-JRC-IES 2010). The system boundary includes the following unit operations: electricity supply, CO_2 capture and supply, electrolysis and methanation, and combustion. The unit process of storage and subsequent application of PtG are ignored, as it is considered as equivalent for all technologies of producing hydrogen and SNG. The combustion (oxidation of the PtG products) is included to form a cradle to grave perspective. The allocation issue occurs when multiple products or functions are delivered by a single unit process or product system. The hierarchy from the ISO 14044 (2006) for solving multi-functionalities require: (i) firstly, use subdivision, by dividing the unit process into two or more sub-processes (ii) if the subdivision is not possible, system expansion by expanding the product system to include the additional functions related to the co-products; (iii) when allocation cannot be avoided, partitioning inputs and outputs in a way that reflects the underlying physical relationships or, if not possible, in a way that reflects other relationships, such as based on economic value, mass or energy content. The further discussion of allocation issue related to CO_2 feedstock is given in section 4.3.4.

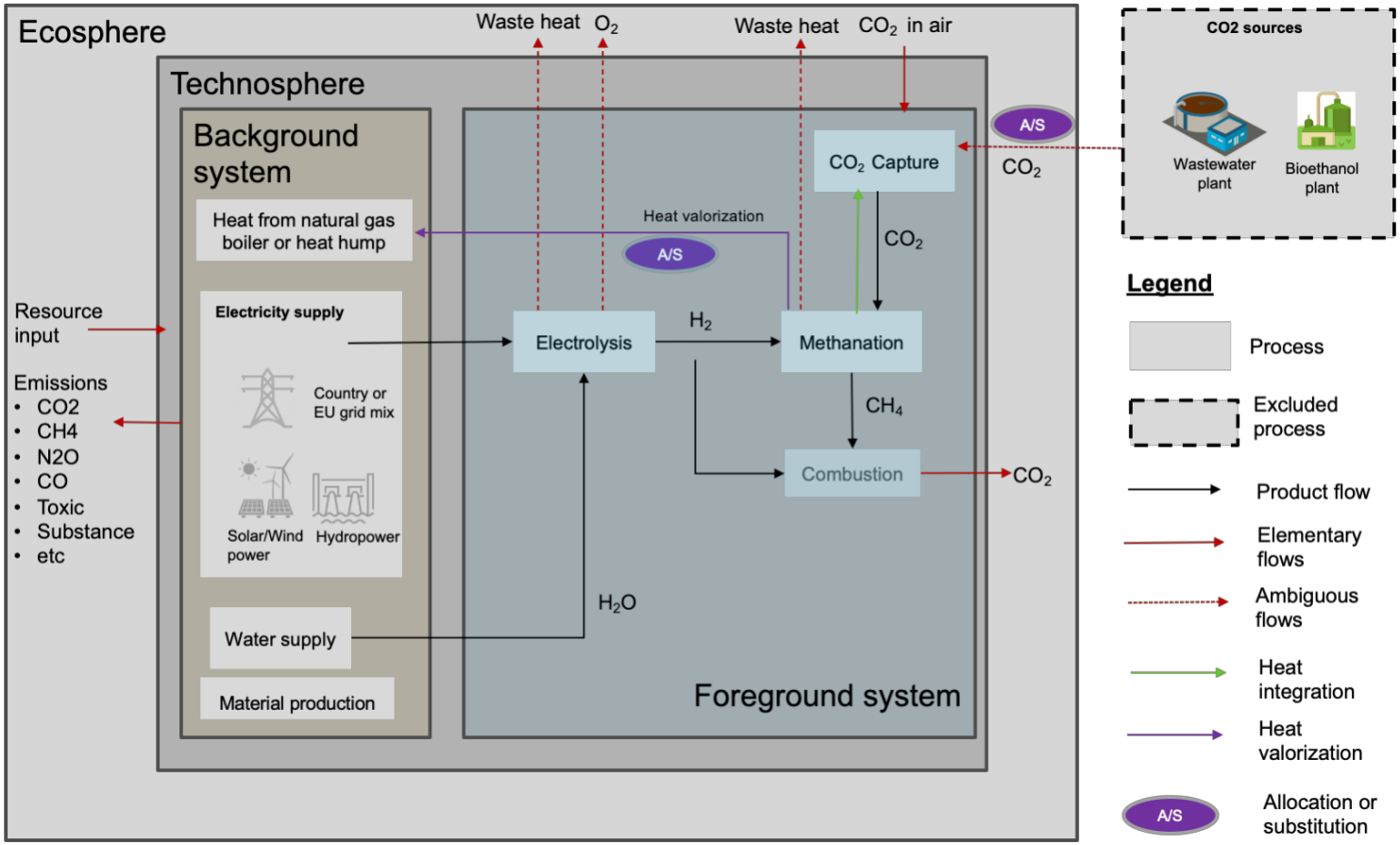

Figure 4.2 System boundary of Power-To-Gas

The elementary flows cross the boundary between the technosphere and ecosphere, while the economic flows stay within the technosphere: i) elementary flows refers to material or energy that entering the system being studied that has been drawn from the environment without previous human transformation or leaving the system being studied that is released into the environment without subsequent human transformation. ii) the economic flow is intermediate product, material or energy flow occurring between unit processes of the product system being studied. iii)Ambiguous flows, occurring from multi-output processes, refers to flows that can be treated as direct emissions in the ecosphere as "elementary flow", a by-product to be managed as a waste or as an intermediate co-product in the technosphere as "economic flow. These flows include waste heat from electrolysis and methanation steps, O_2 produced from electrolysis and CO_2 generated from wastewater plant or bioethanol plant; iv) the heat from electrolysis cannot be valorized currently. The heat from methanation can be valorized for supplying heat for CO_2 capture, and to be sent externally to displace heat otherwise provided by natural gas boiler as a default assumption or heat hump as a sensitivity)

4.3.3 Life cycle inventory analysis

The life cycle inventory analysis (LCI) is an inventory of input/output elementary flows that relates to the functional unit of the system being studied (ISO 14040, 2006). The key primary data of the unit operations (foreground system) described in Figure 4.2 are collected from the managers of the three PtG demonstration sites, with key parameter data reported in Table 4.3. Detailed infrastructure and equipment data are collected for methanation reactors, auxiliary consumables, including the quantity and types of catalyst, process water, nitrogen consumption, and wastewater treatment. Balance of plant (BoP) data consists of the material type and weight of SNG cooling equipment, fans and compressors, heat management module, liquid treatment module, gas treatment modules, CO_2 conditioning unit, piping and valves, electrical panels and cables, and so forth. The secondary LCI data, describing cradle-to-gate emissions and resource consumption of the supplied product of each unit operation (so-called background processes, such as the steel production), are mostly taken from the ecoinvent database (version 3.5). For the electrolyzer modeling, the LCI data from the NEEDs project is used for Alkaline electrolyzer (60 Nm^3/h H_2 production) with the lifetime 80000 hours. The stack LCI data from ecoinvent database is used for PEM electrolyzers, with scale adjustment following the approach in Gerber et al (2011) and a cost capacity factor of 0.7 (the detailed model description is available in Appendix 2). Further consideration of the modeling of the carbon footprint of electricity input and CO_2 feedstock are discussed in the section 4.3.4.

4.3.4 The framework of calculating the carbon footprint of Power-To-Gas

In this section, a general methodological framework for quantifying the carbon footprint of PtG is proposed, including i) the definition and the basic model of calculating the carbon footprint of PtG; ii) the method for modeling the carbon footprint of electricity supply, iii) the method for allocating the carbon footprint accounting of CO_2 feedstock.

4.3.4.1 The basic model for calculating the carbon footprint of PtG

By adapting the definition from Wiedmann and Minx (2008), we define "the carbon footprint is CO_2-equivalent of different greenhouse gases (GHGs) emissions, measured using the global warming potential (GWP) metric with a 100-year time horizon, that are directly and indirectly caused by an activity or is accumulated over the life stages of a product." In LCA, any inventory problem and its solutions can be summarized in equation (4.1) from Heijungs & Suh (2013), where A represents the technology matrix that includes all the intermediate economic flows

(including for example 1 kWh of electricity production, 1 kg of CO_2 feedstock capture, 1 kg of steel production used in the methanation reactor), B stands for the environmental intervention matrix (for example, the CO_2 emissions) , and f represents the final demand, i.e., the function unit defined in the goal and scope (for example, the 1 MJ of hydrogen or 1 MJ of SNG in this study). g stands for the unknown final environmental emissions associated with f. s is a scaling factor vector, which can be found by solving the linear question As= f. The life cycle environmental emissions of a given function unit can be solved with the eq (4.2).

$$\begin{bmatrix} A \\ B \end{bmatrix} s = \begin{bmatrix} f \\ g \end{bmatrix} \tag{4.1}$$

$$g = Bs = BA^{-1}f \tag{4.2}$$

Let C stands for the global warming potentials characterization factors for different GHG emission substances, such as CO_2, CH_4, N_2O and so forth. The $fixed$ global warming potential (GWP) metric based on IPCC 2013 (AR5) is used by default to characterize GHG substance flows. Then, for any product systems, the carbon footprint h , a vector of nx1 with unit of kg CO_2-eq/ MJ of hydrogen and kg CO_2-eq/ MJ of SNG), can be calculated using the equation (4.3). h_i is the carbon footprint "emission factor" of any product i.

$$h = CBA^{-1} f \tag{4.3}$$

However, the basic model described in eq. (4.3) does not explicitly address (i) the multi-regional cross-border product trade, a predominant problem for the electricity market in Europe; (ii) the allocation problem for PtG carbon footprint. They are further discussed in section 4.3.4.2 and 4.3.4.3, respectively.

4.3.4.2 Modeling the carbon footprint of electricity supply

Figure 4.3 illustrates different assumptions for the calculation of electricity carbon footprint (kg CO2-eq/ kWh of electricity) in the matrix A.

a) **Market-based assumption**: when market-based electricity purchasing information is known, a supplier-specific and residual mix emission factors need to be applied to differentiate the tracked certified electricity purchase, such as those with the guarantee of origin (GOO) and untracked residual electricity mix. The tracked amount of electricity purchase is assigned to specific users with certificates. To avoid double-counting the same renewable electricity generation, GHG emissions factors assigned to other users who do not purchase GOOs should then be based on the residual mix

emission factor. A country's residual mix represents the shares of electricity generation attributes available for disclosure, after the use of explicit tracing systems, such as (the) GOO, has been accounted for.

b) **Location-based assumption**: when the market-based information is unknown, a location-based approach can be applied. The modeling of location-based carbon footprint of electricity can be further differentiated into production mix (the domestic mix of electricity generation technologies within a country's territory boundary) and consumption mix from the consumption perspective that considers electricity trade among different regions.

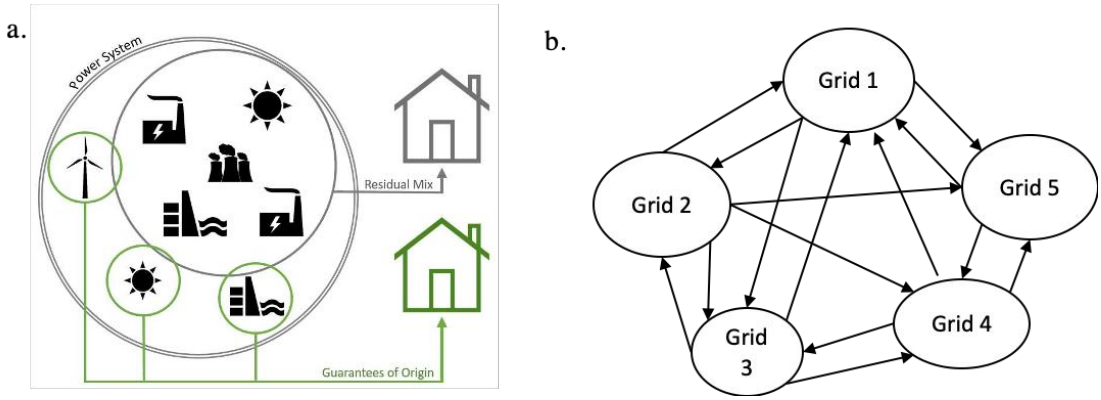

Figure 4.3 Scenarios of electricity supply

a.) Market-based accounting: When a supplier of grid electricity can deliver a specific electricity product with specific life cycle data and guarantee that the electricity sale and the associated GHG emissions are not double-counted, such as the Guarantee of Origin (GO) (RES Directive 2009/28/EC, Art. 15, REDII Directive 2018/2001, Art 19) b.) Physical location-based consumption-mix accounting: Electricity trade network of five grids.

For the **market-based assumption** (case a), h_j [kg CO_2-eq/kWh], the carbon footprint of electricity input for a user j , can be calculated with the eq.(4.4), where the quantity GOO_{ij} [kWh] and emission factor $h_{i,goo}$ [kg CO_2-eq/kWh] represent the supplier-specific information for the type of electricity i , whereas the quantity RES_{kj} [kWh] and emission factor $h_{k,res}$ [kg CO_2-eq/kWh] represent the residual electricity supply type k.

$$h_j = \sum_i GOO_{ij} * h_{i,goo} + \sum_k RES_{kj} * h_{k,res} \quad (4.4)$$

For the **location-based approach** (case b), when there are no cross-border power flow trade activities, the consumption mix of purchased electricity is the same as the production mix of different electricity generation technologies. The carbon footprint of consuming one unit (e.g., 1 kWh) of electricity at a given time is treated the same for all users in a region based on the proportional-sharing rule, calculated with the eq. (4.3). In the other words, the flow of

electricity from origin of production to destination of consumption is on a regional level without differentiating different electricity users.

When there are electricity trades across regions for a chosen spatial scale (hourly, monthly or yearly average), a consumption mix need to be used to consider electricity trade in LCA. As illustrated in Figure 4.3 (b), the electricity trade is often bilateral with the simultaneous exporting and importing of electricity among different regions. Depending on the temporal resolution of power generation and trade data, either hourly or annual average emission factor [kg CO_2-eq/kWh] can be derived. Several methods described in the literature (Li et al. 2013; Qu et al. 2017a,b; Tranberg et al. 2019) describes the estimation of carbon intensity of purchased grid mix considering the electricity flow from countries of origin to countries of consumptions. The multi-regional model is the following: for any region r at a given temporal period t, $let\ z_{rs}$ [kWh] represents the amount of electricity flow exported from the region s to the region r during that time period, z_r [kWh] represents the total amount of electricity flow exported from other regions to the region r during that time period, p_r [kWh] is the amount of production in region r, c_r [kWh] is the amount of consumption in region r. The total electricity supply in region r m_r [kWh] for that given time period t can be modeled by the eq. (4.5), assuming the transmission and distribution loss can be neglected.

$$m_r = p_r + \sum_{s=1}^{n} z_{rs} = c_r + \sum_{s=1}^{n} z_{sr} \tag{4.5}$$

Let $h_{r,cons}$ [kg CO_2-eq/kWh] represents the carbon footprint intensity of the total electricity supply m_r, which is equivalent for the c_r , the electricity consumed in region i, based on the proportional-sharing rule. Then, $h_{r,cons}$ is the carbon footprint emission factor we would like to compute for the region r from the consumption perspective. Let $h_{k,r}$ [kg CO_2-eq/kWh] stand for the carbon emission of different production technology mode k in the region r, $p_{k,r}$ [kWh] the production output of technology mode k in the region r. Let $\widetilde{h_{r,prod}}$ [kg CO_2-eq] stands for the carbon footprint of the total produced electricity in region r, which is the sum of $h_{k,r} * p_{k,r}$. The carbon footprint intensity of the production mix $h_{r,prod}$ [kg CO_2-eq/kWh] can be derived by dividing the $\widetilde{h_{r,prod}} / \sum_{k=1}^{n} p_{k,r}$, where $h_{k,r}$ can be calculated using the eq (4.3) introduced above. Eq. (4.6) to eq. (4.9) below shows how to derive the $h_{r,cons}$.

With the carbon emission balance, the equation (4.5) can be rewritten into the equation (4.6)

$$h_{r,cons}m_r = \sum_{k=1}^{n} h_{k,r*}p_{k,r} + \sum_{s=1}^{n} h_{s,cons}z_{rs} \tag{4.6}$$

With matrix transformation, the set of linear equations derived from the equation (4.6) is equivalent the equation (4.7).

$$\begin{bmatrix} p_{1+Z1} & -z_{12} & \cdots & -z_{1n} \\ -z_{21} & p_{2+Z2} & \ddots & z_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ -z_{n1} & \cdots & z_{n(n-1)} & p_{n+Zn} \end{bmatrix} \begin{bmatrix} h_{1,cons} \\ h_{2,cons} \\ \vdots \\ h_{n,cons} \end{bmatrix} = \begin{bmatrix} \widetilde{h_{1,prod}} \\ \widetilde{h_{2,prod}} \\ \vdots \\ \widetilde{h_{n,prod}} \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{n} h_{k,1*}p_{k,1} \\ \sum_{k=1}^{n} h_{k,2*}p_{k,2} \\ \vdots \\ \sum_{k=1}^{n} h_{k,n*}p_{k,n} \end{bmatrix} \tag{4.7}$$

Let h_{cons} as a n x 1 vector of $h_{r,cons}$. M is a n x n diagonall matrix of $\widehat{m_r}$. Z is a n x n off-diagonal value of z_{rs}. $\widetilde{h_{prod}}$ is a n x 1 vector of $\widetilde{h_{r,prod}}$. Eq. (4.7) can then be summarized into eq. (4.8)

$$(M\text{-}Z)*h_{cons} = \widetilde{h_{prod}} \tag{4.8}$$

By solving the equation (4.8) with standard matrix inversion procedure, the carbon footprint of consuming electricity in all regions can be calculated using the equation (4.9)

$$h_{cons}=(M\text{-}Z)^{-1}\widetilde{h_{prod}} \tag{4.9}$$

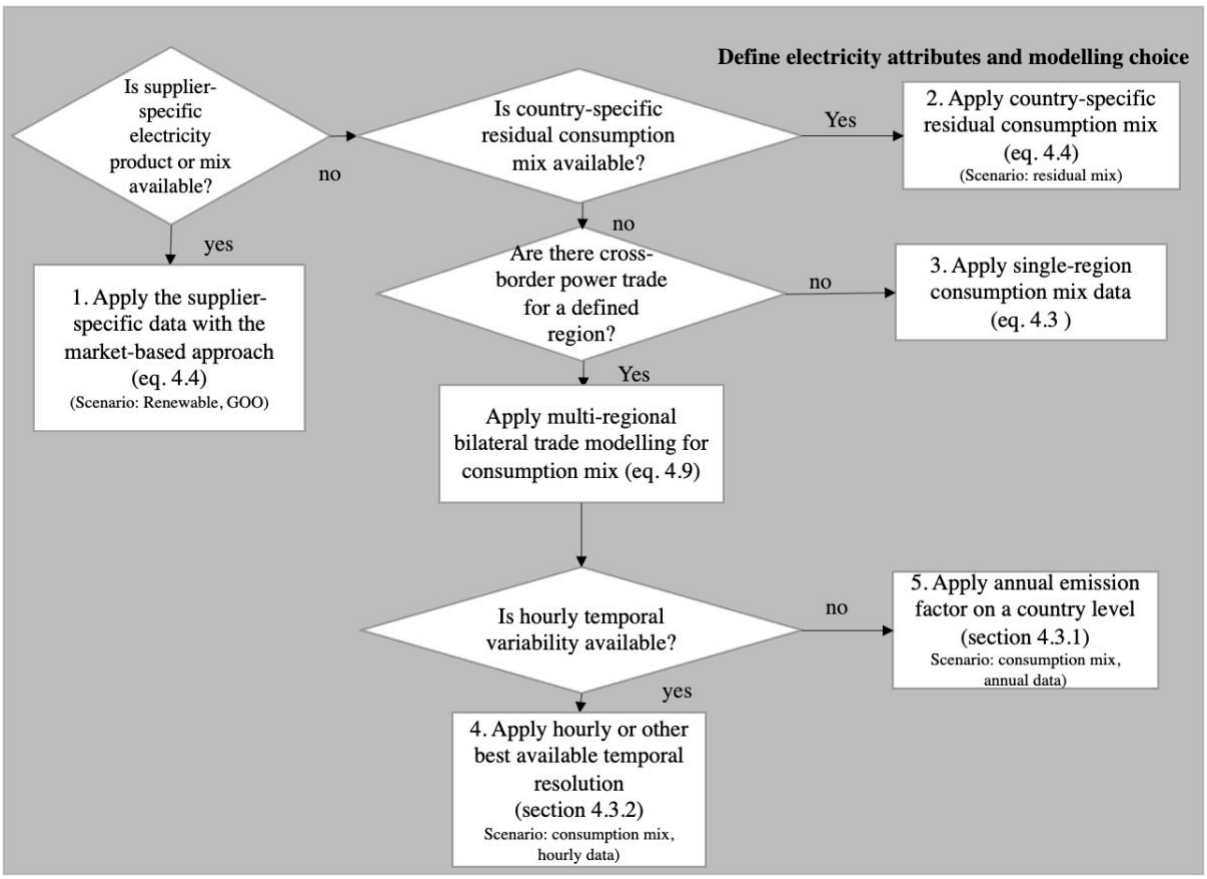

Figure 4.4 The decision tree and method of calculating the carbon footprint of electricity input for PtG.

To facilitate the choice of different supply type and modeling approaches, following the rule of ISO/TS 14067(2013) and EU Product Environmental Footprint Category Rules guidance (European Commission 2018), Figure 4.4 describes the decision tree developed for guiding the calculation of the carbon footprint for the electricity supply. Table 4.4 summarizes different types of electricity supply, modeling choices, data sources and calculation methods, with their influence on the carbon footprint of PtG presented and discussed in section 4.4.4.

Table 4.4 Modelling choices of electricity supply scenarios for PtG

Temporal scale	*Type of electricity*	*Market -based*	*Location based*	*Data source and calculation method*
Annual Average	Supplier specific electricity with GOO (default)	x		Renewable mix reported in Table 1; $h_{i,goo}$ is calculated based on the eq (4.3)
	Residual consumption mix of grid electricity	x		European Residual Mix Association of Issuing Bodies (AIB) (European Residual Mixes 2018 Association of Issuing Bodies 2019) . The $h_{k,res}$ is calculated based on "Issuance Based Residual Mix Calculation Methodology" described by AIB(2020), which assumes the emission factor of imported electricity from country i is the same as emission factor of production mix of the country i.
	Production mix of grid electricity		x	ecoinvent database (both v3.5 and 3.6) (2020) for different reference years, calculated based on eq (4.3)
	Consumption mix of grid electricity		x	
Hourly data	Production mix of of grid electricity		x	Electricity generation technology types, consumption and trade data retrieved from the entso-e (2020) website, by applying the eq. (4.3) to compute the production mix, and by applying eq. (4.9) to compute the consumption mix considering the cross-border power trade in Europe
	Consumption mix of grid electricity		x	

4.3.4.3 Method of allocating the carbon footprint of CO_2 feedstock

Various studies (Weidema 2000, 2003; Suh et al. 2010; von der Assen et al. 2013, 2016; Müller et al. 2020) discussed how allocation should be considered in LCA in general or specific to CO_2 feedstock. However, none of those studies provides explicit guidance on how to tackle ambiguous flows, such as the CO_2 flow used for PtG, which can be either treated as an elementary flow when it was directly emitted to air without capture or as an economic flow when it was captured for use and storage. The application of allocation procedure to CO_2 feedstock is not consistent from the reported literature (Blanco et al. 2020; Zhang et al. 2020; Muller et al. 2020) regarding if the CO_2-based utilization could receive the credits of utilizing the CO_2 or bear the climate burden of the final releasing the molecule carbon from CO_2 feedstock, especially when they are sourced from fossil origins. Furthermore, preferable approach also varies from substitution (Muller et al. 2020), comparative approach (von der Assen et al.; 2016) to economic allocation (Von der Assen, et al.2013) when it comes to evaluate the product-specific carbon footprint of the CO_2 feedstock. Buildings on the work of Weidema (2000), we propose a decision framework in Figure 4.5 to calculate the carbon footprint allocation of CO_2 feedstock for PtG applications. In this framework, two distinctions are made for CO_2 flow based on the reference conditions, (i) whether it was emitted to air directly as elementary flow or captured already for utilization or storage purposes; (ii) whether the captured CO_2 is fully utilized and if there is a competition for utilizing the CO_2 flow.

The existing studies argues system expansion or substitution should be used for calculating the carbon footprint of CO_2 feedstock (Zhang et al. 2017; Muller et al. 2020), yet the use of system expansion and substitution approach is a contentious topic in LCA (Pelletier, et al. 2015; Heijungs et al. 2021). It requires the knowledge of the marginal substitution technology, which is often based on an assumptions or scenarios. For example, both Zhang et al. (2017) and Muller et al. (2020) assumes the current CO_2 feedstock supply systems do not capture CO_2 when system expansion or substitution approach is used. Choosing different assumptions for the substitution or system expansion approach would yield different results (Pelletier, et al. 2015). As illustrated in Figure 4.5, we clarify this assumption might not necessarily hold when there is a constrained competition for CO_2 by the product B, and we argue the subdivision approach is also worthy of consideration when the sourcing CO_2 can be treated as elementary flow "direct release into atmosphere" in the reference condition. When there are no supply constraints of CO_2, the recommended system expansion or substitution approach (Zhang et al. 2017; Muller

et al. 2020) approach correspond to the special case of the subdivision approach in the framework. The application of the method is illustrated in section 4.4.3 below.

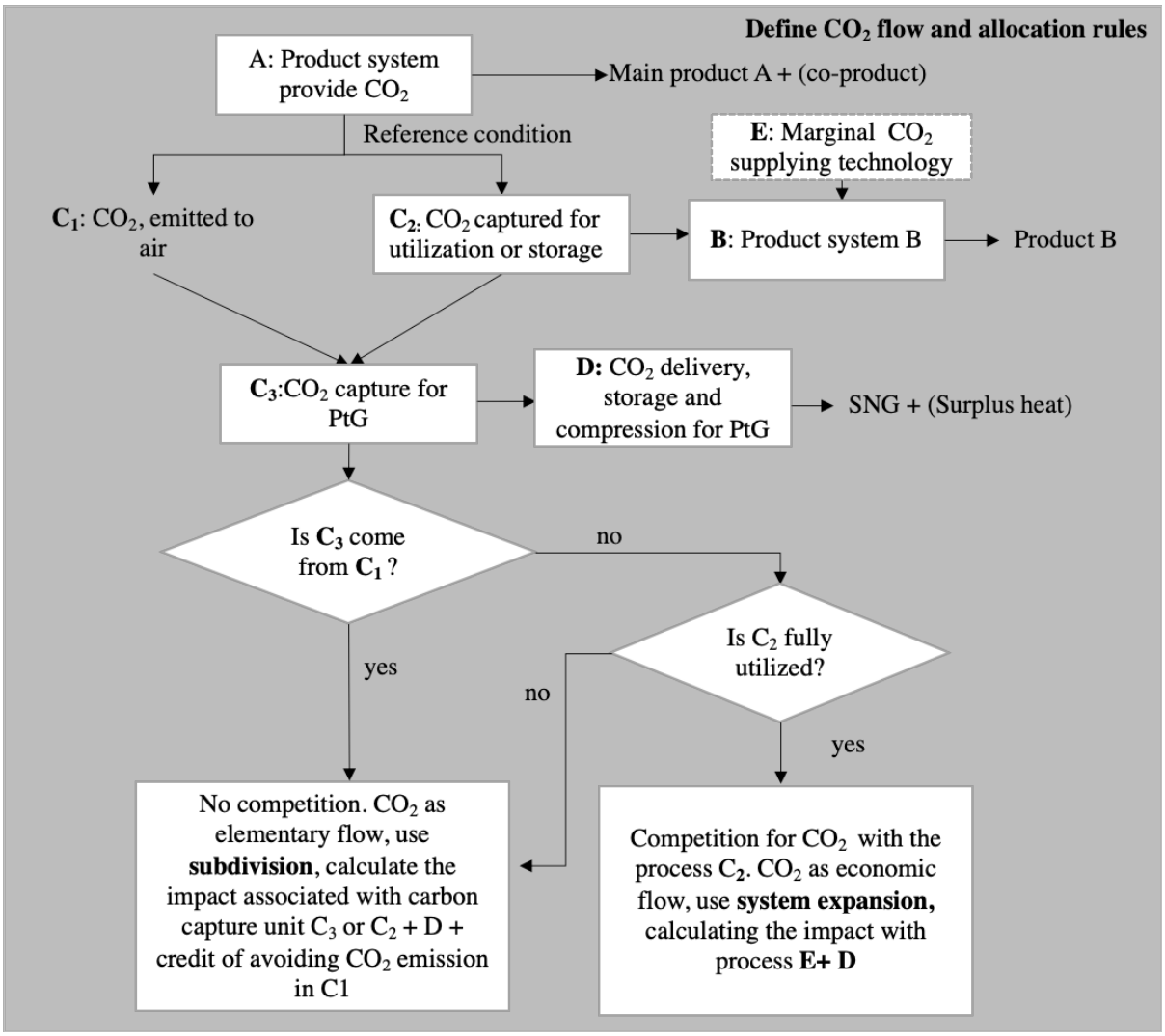

Figure 4.5 Decision tree for calculating the carbon footprint of CO_2 feedstock for PtG

4.4 Result and discussion

The methodology described in section 4.3 is applied for the three pilot demonstration sites. As the CO_2 feedstock for all the demonstration sites in this study belong to the non-competition unconstraint scenario, thus subdivision approach in Figure 4.5 is performed. For the default scenario, renewable electricity with GOO is used for the 3 PtG demonstration sites, with the results reported in section 4.4.1.

4.4.1 Influence of technology choices and regional difference

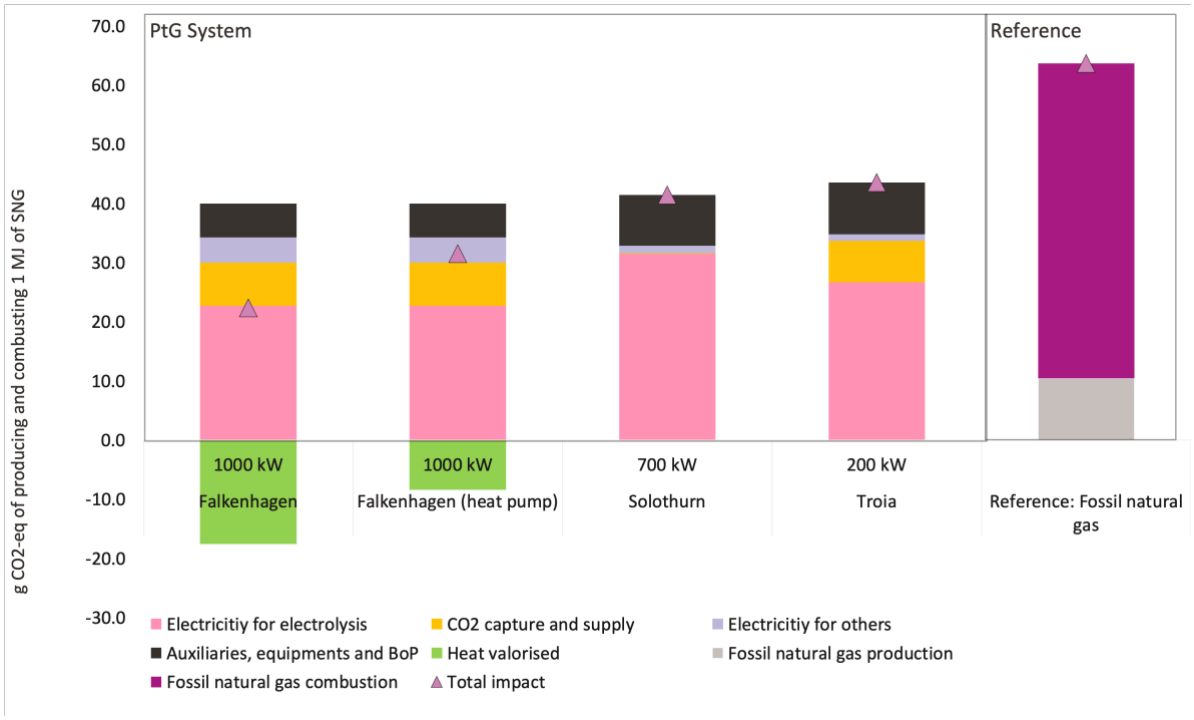

Figure 4.6 Climate change impact of producing and combusting 1MJ of SNG and fossil natural gas

Figure 4.6 shows the climate change impact of producing 1 MJ of SNG from the demonstration plants under different system configurations using renewable electricity sources with GOO. Overall, SNG produced from PtG demonstration sites ranges from 22.4-43.5g CO_2-eq/MJ SNG, a 32-65% reduction of carbon footprint compared to the fossil natural gas (63.7 g CO_2-eq/MJ Natural gas) when powered with renewable electricity inputs. The contribution from the CO_2 capture and supply ranges from 0.1-7.3 g CO_2-eq/MJ SNG. The impact of auxiliaries, equipment and BoP ranges from 5.7-8.8 g CO_2-eq/MJ SNG, which is 18-26% of the overall carbon footprint of PtG. It shows the electrolyzer, reactor and catalyst consumption only contribute to 1.7-1.9 g CO_2-eq/MJ SNG, with majority impact from liquid and gas treatment systems, CO_2 tank storage and conditioning unit, heat management module and process center modules. A more detailed breakdown of carbon footprint is included in Appendix 3. The main variations of different PtG scenarios come from the consideration of heat valorization, energy efficiency of electrolyzers, and options of CO_2 capture, with further analysis by each demonstration plant given below.

- In Falkenhagen, the electricity consumption for electrolysis, with an energy requirement of 4.9 kWhel/m^3-H_2, is the largest impact contributor for the PtG

production system with 22.7 g CO_2-eq/MJ SNG. The liquefaction and transportation of 400 km of the CO_2 feedstock from the bioethanol plant contribute to 7.3 g CO_2-eq/MJ SNG. Electricity for methanation and other processes contributes to 4.2 g CO_2-eq/MJ SNG. The Auxiliary, equipment and BoP contribute to 5.7 g CO_2-eq/ MJ SNG. The Falkenhagen site has the lowest climate impact among all scenarios analyzed, mainly due to the credits of valorizing excess heat that would otherwise be provided by natural gas boilers (17.6 g CO_2-eq/MJ-SNG) or by heat pump (8.4 g CO_2-eq/MJ-SNG).

- In Solothurn site, the electrolysis electricity consumption contributes to 31.5 g CO_2-eq/MJ-SNG, mainly due to a higher electrolyzer energy requirement, 5.8 kWhel/m^3 of H_2. The CO_2 capture and supply contribute to a negligible impact of 0.1 g CO_2-eq/MJ SNG, because (i) the biological methanation reactor can tolerate CO_2 with less purity, reducing the requirement of CO_2 upgrading and purification and (ii) the proximity of the wastewater plant supplying the CO_2. Electricity for methanation and other processes contributes to 1.3 g CO_2-eq/MJ-SNG. The Auxiliary, equipment and BoP contribute to 8.6 g CO_2-eq/MJ-SNG.
- In Troia site, the baseline scenario, electrolysis electricity consumption, with an energy requirement of 4.9 kWhel/m^3 of H_2, contributes to 26.7 g CO_2-eq/MJ-SNG, which is higher than the impact in Falkenhagen albeit with the same efficiency. The reasons are due to two aspects: i) the renewable electricity sourcing mix in Troia has a higher share of PV (60%) than wind (40%) , whereas in Falkenhagen the electricity mix has more wind (70%) than PV (30%); ii) the carbon intensity of wind electricity is lower than that from PV electricity, as shown in Figure A1 in Appendix. The *in-situ* CO_2 by direct air capture (DAC) contributes to 7 g CO_2-eq/MJ SNG, whereby 60% comes from energy consumption related to CO_2 capture, and 40% are related to the DAC equipment. Although the climate impact from CO_2 capture in Troia is similar to that in Falkenhagen, the reason is quite different. In Falkenhagen, the climate impact associated with direct CO_2 capture itself is negligible, and the GHG emissions are mainly due to CO_2 liquefication and long-distance truck transportation. Electricity for methanation and other processes contributes to 1.1 g CO_2-eq/MJ SNG. The Auxiliary, equipment and BoP contribute to 8.8 g CO_2-eq/ MJ SNG.

4.4.2 The threshold of maximum allowable GHG intensity of electricity input

The definition of the threshold of GHG intensity of electricity input varies depending on a chosen target, for example, "to be lower than fossil counterpart" or "to meet a specific regulatory/ compliance requirement". Several prior studies report the GHG reduction requirement under regulatory contexts. Meylan et al. (2017) show that the EU Commission Renewable Energy Directive (RED) (Directive 2009/28/EC) (EU 2009) requires 60% GHG emissions savings compared to traditional fuels, and argues this is not well designed for PtG from a legal perspective, as it does not consider variabilities due to system configurations. Spielmann et al. (2015) show the current EU grid mix for PtG does not meet the GHG reduction requirement in Switzerland for the mineral oil tax exemption (Swiss Federal Customs Administration FCA 2017) that requires at least 40% reduction of GHG emissions compared to the life cycle impact of traditional fuels. Koponen et al. (2017) shows the carbon intensity of electricity used to produce hydrogen is a key factor to achieve 70% emission saving compared to fossil fuels required by RED 2 (Directive (EU) 2018) set by the European commission in 2018 (EC 2018).

The threshold value is thus important to consider, however large variabilities of the threshold values are reported in the literature. In this study, we define the threshold of electricity carbon intensity is to obtain SNG with lower emission intensity than fossil natural gas (63.7 g CO_2-eq/MJ Natural gas). We estimate the threshold of carbon footprint intensity for electricity input should not exceed the range of 86-155 g CO_2-eq/kWh in a general PtG production system, taking into the system efficiency variations and potential heat valorization opportunities, as well as the variability of carbon emissions of infrastructure and equipment obtained from the pilot demonstration sites. The premise for this result assumes that the sourcing CO_2 feedstock used by PtG can be taken without the burden of CO_2 emissions of the molecule carbon in the CO_2 feedstock. The variations of threshold values are mainly due to system energy efficiencies and heat valorization. Our estimate is close to the range of 73-181 g CO_2-eq/kWh reported in the relevant studies (see Table 4.2). The life cycle carbon footprint of renewable electricity technologies with GOO, based on the data reported in IPCC 2014 (Schlömer et al. 2014), are generally under the threshold range reported in this study. However, nowadays majority of purchased grid electricity cannot meet this threshold value according to the worldwide country-specific carbon intensity estimation of electricity estimated by Qu et al (2018).

Assuming the electrolysis efficiency range (50 – 65 kWh /kg H_2) and the 100 grams CO_2-eq/kg-H_2 related to infrastructure and equipment of PtH calculated in this study, we estimate the threshold of electricity input for H_2 from PtH production systems is 215-280 g CO_2-eq/kWh, to be less than the carbon footprint of H_2 production from steam reforming from fossil natural gas (14.08 kg CO_2-eq/kg H_2). By varying the benchmarking carbon footprint of H_2 production steam reforming from fossil natural gas (10.92 to 15.96 kg CO_2-eq/kg H_2, as reported in Appendix 1), the threshold can be extended to 166-317 g CO_2-eq/kWh. Our estimate for PtH does not consider the potential credits from the co-products (heat and O_2), as they are currently difficult to valorize. In comparison, Reiter and Lindorfer (2015) reports the threshold of PtH should not exceed 190 g CO_2-eq/kWh. This lower threshold estimation ignores the electrolysis efficiency variabilities and considers a lower reference value for hydrogen, 10.92 kg CO_2-eq/kg-H_2. In this section, we show the threshold value is sensitive to the choice of reference benchmarking fossil counterpart and the system variations of PtG production systems. This should be considered when designing a regulatory climate policy for clean fuel incentives.

4.4.3 Influence of CO_2 feedstock accounting and allocation approaches

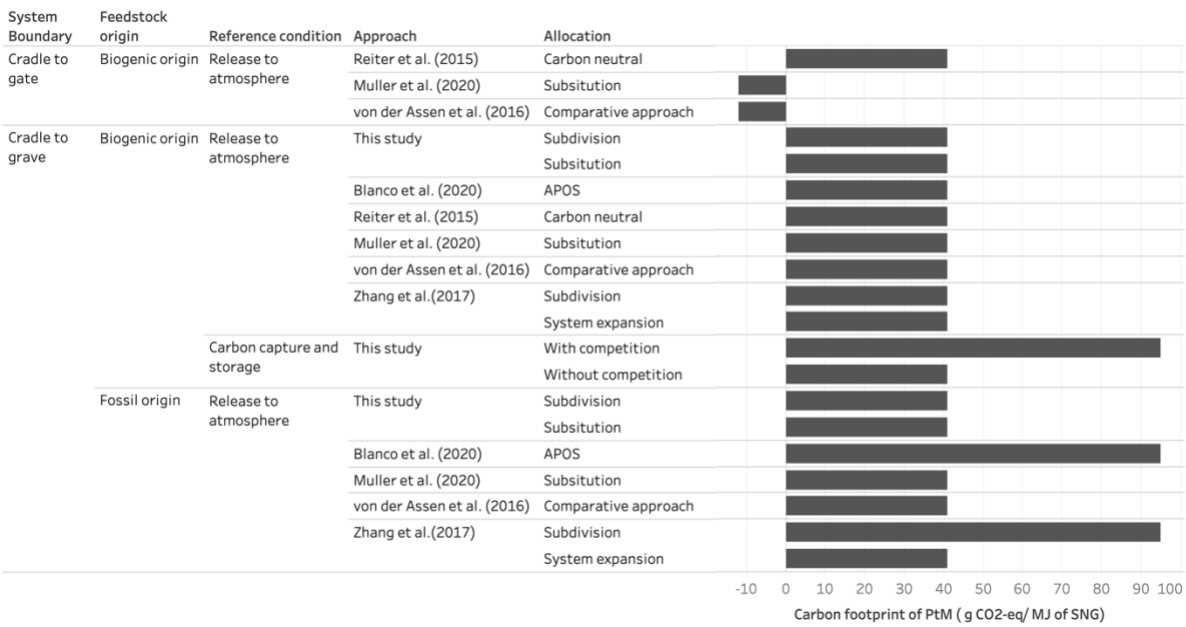

Figure 4.7 Comparison of the carbon footprint of PtG from different allocation approaches, system boundaries, feedstock origin and reference conditions

The approach of accounting of CO_2 feedstock used by PtG varies due to different allocation approaches (Blanco et al. 2020; Zhang et al. 2020; Muller (2020), especially when it comes to different CO_2 sourcing origins. The debate and inconsistency of treating CO_2 feedstock also

have policy implications For example, in the Italian support scheme for biomethane as transportation fuel, SNG can only use carbon from a biogenic source, whereas in Switzerland, the support for SNG used for vehicles can only consider ambient air capture (Kreeft 2018). Figure 4.7 shows the carbon footprint of PtM of Solothurn PtG demonstration site under different approaches and assumptions related to the CO_2 feedstock accounting. In this illustrate example, we considered different system boundaries, CO_2 sourcing origin, reference conditions, allocation and accounting approaches proposed in the literature. The additional results for "this study" are generated according to the modeling framework proposed in section 4.3.4. It shows in a "cradle-to-grave" system boundary, there is a global consensus of the carbon footprint of SNG if the CO_2 feedstock is sourced from biogenic origin that would otherwise be released to atmosphere. The term "reference condition" is equivalent to the "status quo" used by von der Assen et al. (2016). Most literature assumes the status quo is direct release of CO_2 without carbon capture. Our analysis show that the choice of subdivision, system expansion or substitution are equivalent with this reference condition for CO_2 sourced from the biogenic origins. Disagreement emerges when the system boundary is narrowed to "cradle to gate" for modeling biogenic CO_2 sequestered in a short-life intermediate product (SNG) or the CO_2 is sourced from fossil origin. Overall, for the CO_2 sourced from fossil origin, results using substitution/ system expansion converge when the system boundaries are "cradle to grave". In conclude, we argue the carbon footprint modeling of CO_2 feedstock used for PtG should focus on the reference condition rather than its sourcing origin (biogenic vs fossil). The preferable allocation approach is subdivision or system expansion /substitution. To avoid the debate of negative credits or "carbon neutral" for the CO2 sequestered in the intermediate product, the system boundary is recommended to include the impact of the final oxidation of SNG.

4.4.4 Influence of electricity modeling

4.4.4.1 Effect of electricity modeling with annual emission factors

For estimating the carbon footprint of electricity supply, two approaches are examined, namely, location-based and market-based. For the location-based approach, the results from production and consumption perspective are differentiated. For the market-based approach, supplier-specific (renewables, GOO) and residual consumption mix scenarios are differentiated. Swiss mineral tax exemption requires 40% lower carbon footprint than fossil alternative. Figure 4.8 shows the influence of electricity supplying scenarios and modeling approaches according to Table 4.4, with further explanations provided in Table 4.5.

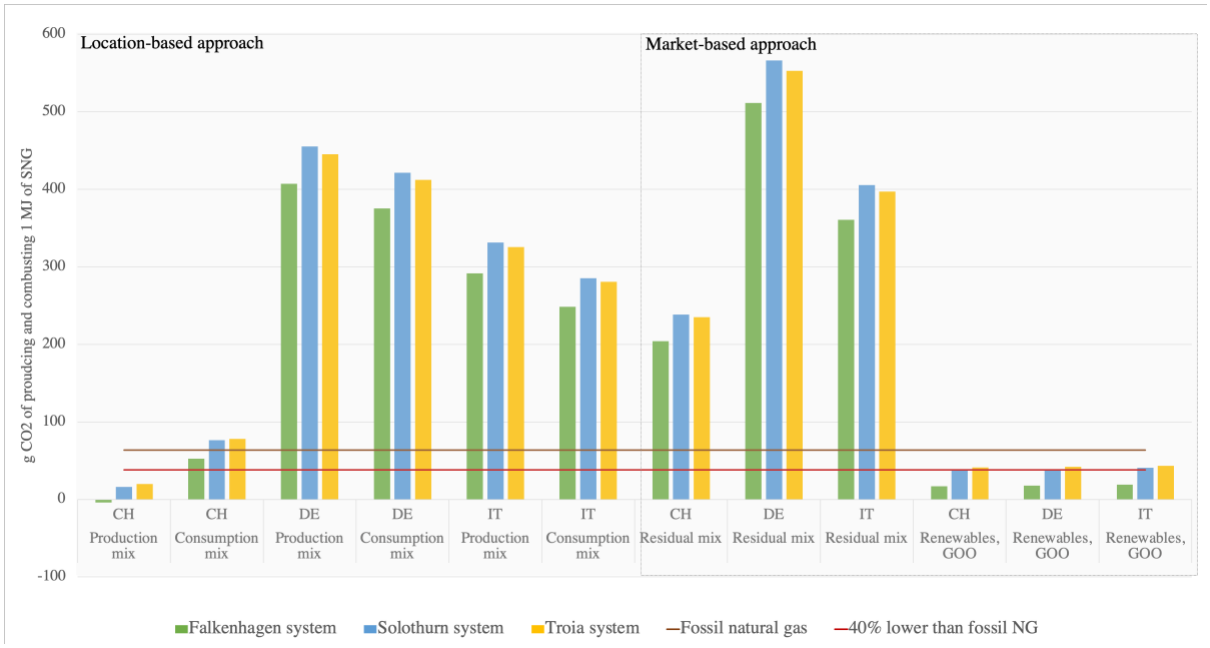

Figure 4.8 Influence of electricity supply scenarios and modeling choices on the carbon footprint of PtG. Three PtG production systems are analyzed, including Falkenhagen, Solothurn and Troia. For each production system, electricity supply of three selected countries (Switzerland-CH, Germany-DE, Italy-IT) is analyzed.

Table 4.5 Feasibility of SNG's emission factors to be lower or at least 40% lower than fossil natural gas

Criteria		Lower than fossil natural gas			40% lower than fossil natural gas (Swiss Mineral Tax exemption)		
Hierarchy of electricity supply modeling	Location	Falkenhagen	Solothurn	Troia	Falkenhagen	Solothurn	Troia
Supplier-specific renewable mix with GOO	CH	yes	yes	yes	yes	yes	no
	DE	yes	yes	yes	yes	no	no
	IT	yes	yes	yes	yes	no	no
Country-specific residual consumption mix	CH	no	no	no	no	no	no
	DE	no	no	no	no	no	no
	IT	no	no	no	no	no	no
Country-specific consumption mix	CH	yes	no	no	no	no	no
	DE	no	no	no	no	no	no
	IT	no	no	no	no	no	no
Country-specific production mix	CH	yes	yes	yes	yes	yes	yes
	DE	no	no	no	no	no	no
	IT	no	no	no	no	no	no

It shows PtG will have a higher carbon footprint than fossil natural gas for most electricity supplying scenarios of the three countries of interests. When the electricity is supplied with three supplier-specific renewable electricity with GOO, all PtG production systems have a lower carbon footprint than fossil natural gas, however they do not necessarily meet the 40% emission reduction to be eligible for the Swiss mineral tax exemption for clean fuel. When the PtG is running through the grid mix, choosing different modeling principles for estimating the carbon footprint of grid mix could lead to different conclusions. The Swiss grid scenario shows the results become more sensitive to the grid mix modeling choice when the grid mix is more decarbonized. Following the proposed decision framework in Figure 4.4, when supplier-specific data is missing, the country-specific residual consumption mix is used. In this case, only the Falkenhagen PtG production system or technology archetype with heat valorization using the GOO-backed renewable electricity mix could meet the 40% emission reduction requirement required by the current Swiss mineral oil tax exemption.

4.4.4.2 Effect of considering hourly differentiated regionalized emission factor

By increasing the temporal scale from annual average to hourly resolution, we further investigate the influence of spatiotemporal variability of electricity GHG emission intensity on the overall PtG impact. Figure 4.9 shows the hourly electricity emission factor in relation to emission thresholds for Germany, Switzerland and Italy from both production and consumption mix perspective for the year 2018 by applying eq. (4.3) and eq. (4.9) respectively based on data retrieved from the entso-e (2020) website, which gives hourly electricity generation volume (MW) by technology types and cross border trade volume (MW). It shows the potential hours during a year to run PtG to have a lower carbon footprint than its fossil counterpart. During most of the hours over the year in Germany and Italy, use of the current grid mix leads to the exceedance of the target GHG intensity ("threshold") for having a lower life cycle GHG emissions than their fossil counterparts, regardless of the production or consumption perspective. However, for Switzerland, the choice of production mix and consumption mix shows a significant difference. This is because Switzerland imports and exports a large amount of electricity over the year and the carbon intensity of imports is higher than the domestic production. It also implies the production of PtG based on grid mix could lead to even higher carbon footprint in Switzerland around about 50% or more of time in a year, even if the yearly average data shows a lower carbon footprint for the PtG production. During the summertime

(the green to blue color), the electricity supply in Switzerland generally has a lower GHG emission intensity.

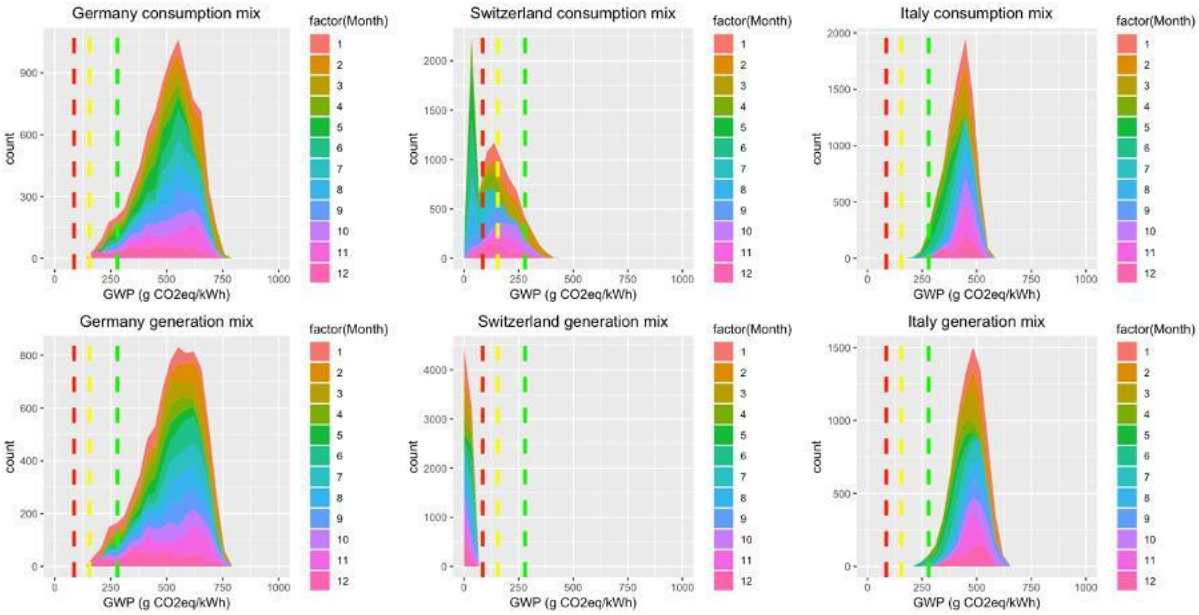

Figure 4.9 Hourly electricity emission factors in relation to emission thresholds

Data are plotted on a monthly scale. Green line: the threshold for PtH (280 g CO_2-eq/kWh); yellow line: upper threshold for PtM(155 g CO_2-eq/kWh); red line: lower threshold for PtM(86 g CO_2-eq/kWh).

4.5 Conclusions and recommendations

In conclude, we proposed a systematic methodological framework to improve the evaluation of the carbon footprint of PtG in this study. The proposed decision trees would help the choices of grid electricity modeling and CO_2 allocation when assessing the carbon footprint of PtG evaluation. Key conclusions and recommendations are made as follows:

- **CO_2 feedstock allocation.** Most studies assume the current CO_2 sources are directly released to atmosphere without capture, therefore, the carbon footprint results converge to the same value regardless of how the recommended approach is called, from substitution (Muller et al. 2020), subdivision (this study), system expansion (Zhang et al. 2017), comparative approach (von der Assen et al. 2016) to carbon neutral (Reiter et al. 2015). The underlying reasoning for this is because they all use the same reference condition or assumption of the current status quo. Our analyses show the importance of clarifying the reference condition or status quo of the CO_2 sources, whether it is non-competitive use, such as direct release to atmosphere or competitive use. The choice of CO_2 for PtG should not be based on its origins (fossil, biogenic or ambient). We recommend the preferable allocation approach is subdivision or system expansion

/substitution. We estimate the impact from CO_2 capture and supply ranges from 0.1-7.3 g CO_2-eq/MJ SNG. Leveraging heat integrations for direct air capture and location proximity to the CO_2 sources can lower the overall energy demand and carbon footprint for capturing and delivering CO_2 for the PtG applications.

- **Grid modeling choices**. When the electricity input is supplier by grid electricity, we show the carbon footprint of SNG from PtG becomes more sensitive to the choices of electricity modeling approaches when a country's grid mix is more decarbonized. We show the importance of considering a finer (hourly or seasonal) temporal scale instead of an annual average when estimating the PtG carbon footprint and its utilization potentials, as the production of PtG could lead to even higher carbon footprint around about 50% or more of time in a year compared to its fossil counterpart, even if the yearly average emission factor shows a lower carbon footprint for the PtG production. Thus, arbitrary choices of electricity grid mix modeling approaches could lead to different and potentially misleading conclusions. In practice, the feasible operating hours (with a lower carbon footprint than reference fossil counterpart) also depend on operating profiles of a PtG production system, availability of unused surplus electricity, and utilization scenarios of final product. However, these analyses are beyond the scope of the current study. When powered with renewable electricity inputs with GOO, we estimated the carbon footprint of SNG produced from PtG demonstration sites (22.4-43.5g CO_2-eq/MJ SNG) have a 32-65% reduction compared to the fossil natural gas (63.7 g CO_2-eq/MJ Natural gas). The variations are due to the difference of leveraging the opportunities of heat valorization, choice of electrolyzers and methanation reactor technologies, and options of CO_2 capture from the three representative PtG demonstration plants covering typical combinations of technology choices for methanation and electrolysis, CO_2 sourcing options and system variations.

Appendix

Appendix 1. Review of life cycle GHG emissions of H_2 and natural gas production

Table A1 Review of life cycle GHG emissions of H_2 and natural gas production (kg CO_2-eq/kg product)

Reference	Product	kg CO_2 eq/kg	Feedstock	Source of feedstock	Technology
Hajjaji 2016	H_2	5.59	biogas	Anaerobic digestion	Steam reforming
Battista 2017	H_2	7.24	biogas	Anaerobic digestion	BioRobur ATR
Reiter 2015	H_2	14.28	Crude oil	Fossil Sources	Steam reforming
Reiter 2015	H_2	10.92	Natural gas	Fossil Sources	Steam reforming
Cetinkaya 2012	H_2	11.84	Natural gas	Fossil Sources	Steam reforming
NREL. 2001	H_2	12.18	Natural gas	Fossil sources	Steam reforming
DEMCAMER 2015	H_2	14.08	Natural gas	Fossil Sources	Steam reforming
Zhang 2017	H_2	15.96	Natural gas	Fossil Sources	Steam reforming
Verma 2015	H_2	0.91	Coal	Fossil Sources	Gasification with CCS
Cetinkaya 2012	H_2	11.3	Coal	Fossil Sources	Gasification
Verma 2015	H_2	18	Coal	Fossil Sources	Gasification
Zhang 2017	H_2	23.04	Coal	Fossil Sources	Gasification
Cetinkaya 2012	H_2	12.3	n.s	Fossil Sources	Cu–Cl cycle
Zhang 2017	H_2	8.17	CH mix supply	Grid mix	AEL
Zhang 2017	H_2	7.21	CH mix supply	Grid mix	PEM
Zhang 2017	H_2	31.92	ENTSO-E	Grid mix	AEL
Zhang 2017	H_2	29.76	ENTSO-E	Grid mix	PEM
Zhang 2017	H_2	27.60	EU 27 mix	Grid mix	n.s
Bareiß 2019	H_2	29.5	Germany 2017	Grid mix	PEM
Bareiß 2019	H_2	11.5	Germany 2050	Grid mix	PEM
Bareiß 2019	H_2	3.3	Surplus	Renewable	PEM
Cetinkaya 2012	H_2	0.97	Wind	Renewable	Water electrolysis
Reiter 2015	H_2	0.60	Wind	Renewable	n.s
Cetinkaya 2012	H_2	2.41	PV	Renewable	Water electrolysis
Reiter 2015	H_2	3.00	PV	Renewable	n.s
This study	NG	2.92	Natural gas	Fossil, GLO, ecoinvent	Extraction+combustion
Reiter 2015	NG	3.21*	Natural gas	Fossil, EU-27, Gabi	Extraction+combustion
Blanco 2020	NG	2.69-3.95**	Natural gas	Fossil, ecoinvent	Extraction+combustion
Reiter 2015	SNG	0.30	Wind	Renewable	PtG
Reiter 2015	SNG	1.45	Wind	Renewable	PtG
Reiter 2015	SNG	1.50	PV	Renewable	PtG
Reiter 2015	SNG	2.65	PV	Renewable	PtG
Reiter 2015	SNG	13.80	EU 27 mix	Grid mix	PtG
Reiter 2015	SNG	14.95	EU 27 mix	Grid mix	PtG

Abbreviations: n.s=not specified
*0.46 kg CO2eq-kg of natural gas supply, 2.75 kg CO2 eq. direct emissions per combustion of 1 kg of natural gas
**58-85 g CO_2eq/MJ is the reported value in Blanco et al. (2020). The conversion is done based on 39 MJ/m^3 and 0.84 kg/m^3

Appendix 2. Scaling approach for process equipment and balance of plant

The scale difference is based on the approach introduced by Leda Gerber et al (2011) as introduced below. The impact of equipment 2 can be estimated based on the formula below

$$\frac{LCA_2}{LCA_1} = (\frac{A_1}{A_2})^b$$

LCA1: environmental impact of equipment 1 (known)

LCA2: environmental impact of equipment 2 (unknown)

A1: scale of equipment 1

A2: scale of equipment 2

b- scaling factor, "cost capacity factor"

In general, a scaling factor of 0.7 is assumed

Appendix 3. Carbon footprint breakdown of auxiliary equipment and BoP

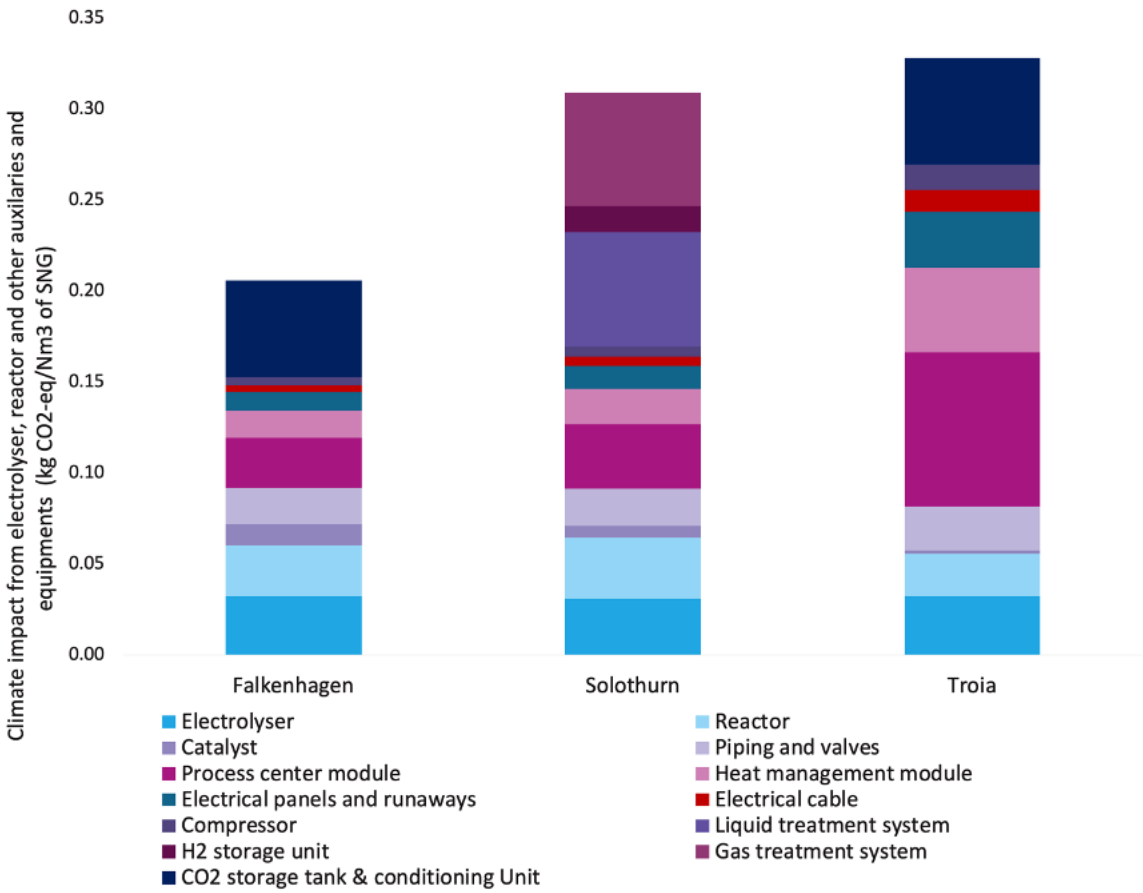

Figure A1. Carbon footprint break down of auxiliary inputs and equipment

Reference

AIB (2020) Revised Residual Mix calculation methodology (from 2020) RM EAM IB Calculation Methodology V1_0.pdf. https://www.aib-net.org/sites/default/files/assets/facts/residual-mix/2019/RM%20EAM%20IB%20Calculation%20Methodology%20V1_0.pdf. Accessed 24 Aug 2020

Albrecht FG, König DH, Baucks N, Dietrich R-U (2017) A standardized methodology for the techno-economic evaluation of alternative fuels – A case study. Fuel 194:511–526. https://doi.org/10.1016/j.fuel.2016.12.003

Assen N von der, Jung J, Bardow A (2013) Life-cycle assessment of carbon dioxide capture and utilization: avoiding the pitfalls. Energy Environ Sci 6:2721–2734. https://doi.org/10.1039/C3EE41151F

Assen N von der, Müller LJ, Steingrube A, et al (2016) Selecting CO2 Sources for CO2 Utilization by Environmental-Merit-Order Curves. Environ Sci Technol 50:1093–1101. https://doi.org/10.1021/acs.est.5b03474

Bailera M, Lisbona P, Romeo LM, Espatolero S (2017) Power to Gas projects review: Lab, pilot and demo plants for storing renewable energy and CO2. Renewable and Sustainable Energy Reviews 69:292–312. https://doi.org/10.1016/j.rser.2016.11.130

Bareiß K, de la Rua C, Möckl M, Hamacher T (2019) Life cycle assessment of hydrogen from proton exchange membrane water electrolysis in future energy systems. Applied Energy 237:862–872. https://doi.org/10.1016/j.apenergy.2019.01.001

Battista F, Montenegro Camacho YS, Hernández S, et al (2017) LCA evaluation for the hydrogen production from biogas through the innovative BioRobur project concept. International Journal of Hydrogen Energy 42:14030–14043. https://doi.org/10.1016/j.ijhydene.2016.12.065

Blanco H, Codina V, Laurent A, et al (2020) Life cycle assessment integration into energy system models: An application for Power-to-Methane in the EU. Applied Energy 259:114160. https://doi.org/10.1016/j.apenergy.2019.114160

Blanco H, Faaij A (2018) A review at the role of storage in energy systems with a focus on Power to Gas and long-term storage. Renewable and Sustainable Energy Reviews 81:1049–1086. https://doi.org/10.1016/j.rser.2017.07.062

Brander M, Gillenwater M, Ascui F (2018) Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. Energy Policy 112:29–33. https://doi.org/10.1016/j.enpol.2017.09.051

Brown T, Schlachtberger D, Kies A, et al (2016) Sector-Coupling in a Simplified Model of a Highly Renewable European Energy System. 59

Buttler A, Spliethoff H (2018) Current status of water electrolysis for energy storage, grid balancing and sector coupling via power-to-gas and power-to-liquids: A review.

Renewable and Sustainable Energy Reviews 82:2440–2454. https://doi.org/10.1016/j.rser.2017.09.003

Castellani B, Rinaldi S, Bonamente E, et al (2018a) Carbon and energy footprint of the hydrate-based biogas upgrading process integrated with CO2 valorization. Science of The Total Environment 615:404–411. https://doi.org/10.1016/j.scitotenv.2017.09.254

Castellani B, Rinaldi S, Morini E, et al (2018b) Flue gas treatment by power-to-gas integration for methane and ammonia synthesis – Energy and environmental analysis. Energy Conversion and Management 171:626–634. https://doi.org/10.1016/j.enconman.2018.06.025

Cetinkaya E, Dincer I, Naterer GF (2012) Life cycle assessment of various hydrogen production methods. International Journal of Hydrogen Energy 37:2071–2080. https://doi.org/10.1016/j.ijhydene.2011.10.064

Collet P, Flottes E, Favre A, et al (2017) Techno-economic and Life Cycle Assessment of methane production via biogas upgrading and power to gas technology. Applied Energy 192:282–295. https://doi.org/10.1016/j.apenergy.2016.08.181

DEMCAMER (2015) Demcamer - Catalytic Membrane Reactors-DEMCAMER-WP9-D92-DLR-Quantis-150820_V2.2. http://www.demcamer.org/. Accessed 26 Sep 2018

Deutz S, Bongartz D, Heuser B, et al (2018) Cleaner production of cleaner fuels: wind-to-wheel – environmental assessment of CO2-based oxymethylene ether as a drop-in fuel. Energy Environ Sci 11:331–343. https://doi.org/10.1039/C7EE01657C

EC (2018) Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. Official Journal of the European Union 5:82–209

ecoinvent (2020) ecoinvent Version 3.5. https://www.ecoinvent.org/database/database.html. Accessed 6 Jul 2020

Electrochaea.dk ApS (2017) Power-to-Gas via Biological Catalysis (P2G-Biocat) ANNEX 1 ForskEL 2014-1-12164 Life Cycle Analysis

ENTSO-E (2020) ENTSO-E Transparency Platform. https://transparency.entsoe.eu/dashboard/show. Accessed 6 Jul 2020

EU (2009) Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. Official Journal of the European Union 5:2009

EU-JRC-IES (2010) International Reference Life Cycle Data System (ILCD) Handbook - General guide for Life Cycle Assessment - Detailed guidance. First edition March 2010. EUR 24708 EN. Luxembourg. Publications Office of the European Union

European Commission (2018) PEFCR Guidance document, - Guidance for the development of Product Environmental Footprint Category Rules (PEFCRs), version 6.3, December 15 2017

European Residual Mixes 2018 Association of Issuing Bodies (2019) European Residual Mixes Results of the calculation of Residual Mixes for the calendar year 2018

Gahleitner G (2013) Hydrogen from renewable electricity: An international review of power-to-gas pilot plants for stationary applications. International Journal of Hydrogen Energy 38:2039–2061. https://doi.org/10.1016/j.ijhydene.2012.12.010

Gerber L, Gassner M, Maréchal F (2011) Systematic integration of LCA in process systems design: Application to combined fuel and electricity production from lignocellulosic biomass. Computers & Chemical Engineering 35:1265–1280. https://doi.org/10.1016/j.compchemeng.2010.11.012

Ghaib K, Ben-Fares F-Z (2018) Power-to-Methane: A state-of-the-art review. Renewable and Sustainable Energy Reviews 81:433–446. https://doi.org/10.1016/j.rser.2017.08.004

Götz M, Lefebvre J, Mörs F, et al (2016a) Renewable Power-to-Gas: A technological and economic review. Renewable Energy 85:1371–1390. https://doi.org/10.1016/j.renene.2015.07.066

Götz M, Lefebvre J, Mörs F, et al (2016b) Renewable Power-to-Gas: A technological and economic review. Renewable Energy 85:1371–1390. https://doi.org/10.1016/j.renene.2015.07.066

Hajjaji N, Martinez S, Trably E, et al (2016) Life cycle assessment of hydrogen production from biogas reforming. International Journal of Hydrogen Energy 41:6064–6075. https://doi.org/10.1016/j.ijhydene.2016.03.006

Heijungs R, Suh S (2013) The Computational Structure of Life Cycle Assessment. Springer Science & Business Media

Hoppe W, Bringezu S (2016) Vergleichende Ökobilanz der CO2-basierten und konventionellen Methan- und Methanolproduktion. uwf 24:43–47. https://doi.org/10.1007/s00550-016-0389-4

Hoppe W, Thonemann N, Bringezu S (2018) Life Cycle Assessment of Carbon Dioxide–Based Production of Methane and Methanol and Derived Polymers. Journal of Industrial Ecology 22:327–340. https://doi.org/10.1111/jiec.12583

IPCC (2018) Global Warming of 1.5° C: An IPCC Special Report on the Impacts of Global Warming of 1.5° C Above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty. Intergovernmental Panel on Climate Change

ISO 14040 (2006) ISO 14040:2006, Environmental management — Life cycle assessment — Principles and framework

ISO 14044 (2006) ISO 14044:2006 - Environmental management -- Life cycle assessment -- Requirements and guidelines

ISO/TS 14067 (2013) ISO/TS 14067:2013(en), Greenhouse gases — Carbon footprint of products — Requirements and guidelines for quantification and communication

Jacobson MZ, Delucchi MA (2011) Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials. Energy Policy 39:1154–1169. https://doi.org/10.1016/j.enpol.2010.11.040

Jentsch M, Trost T (2014) Analyse von Power-to-Gas-Energiespeichern im regenerativen Energiesystem

Jess A (2016) CHEMTEC: Technologien für Nachhaltigkeit und Klimaschutz: chemische Prozesse und stoffliche Nutzung von CO2: sunfire: Herstellung von Kraftstoffen aus CO2 und H2O unter Nutzung regenerativer Energie: Schlussbericht: Sammelbericht aller Teilprojekte. Universität Bayreuth, Fakultät für Angewandte Naturwissenschaften, Lehrstuhl …

KIT (2017) HELMETH - Deliverable 5.2: Final LCA Report. Karlsruhe: Karlsruhe Institute of Technology (KIT) version. R.1.0. Date: 14/06/2017

Klimscheffskij M, Van Craenenbroeck T, Lehtovaara M, et al (2015) Residual Mix Calculation at the Heart of Reliable Electricity Disclosure in Europe—A Case Study on the Effect of the RE-DISS Project. Energies 8:4667–4696. https://doi.org/10.3390/en8064667

Koj JC, Wulf C, Linssen J, et al (2018) Utilisation of excess electricity in different Power-to-Transport chains and their environmental assessment. Transportation Research Part D: Transport and Environment 64:23–35. https://doi.org/10.1016/j.trd.2018.01.016

Koj JC, Wulf C, Zapp P (2019) Environmental impacts of power-to-X systems - A review of technological and methodological choices in Life Cycle Assessments. Renewable and Sustainable Energy Reviews 112:865–879. https://doi.org/10.1016/j.rser.2019.06.029

Koponen K, Hannula I (2017) GHG emission balances and prospects of hydrogen enhanced synthetic biofuels from solid biomass in the European context. Applied Energy 200:106–118. https://doi.org/10.1016/j.apenergy.2017.05.014

Kreeft G (2018) Legislative and Regulatory Framework for Power-to-Gas in Germany, Italy and Switzerland. STORE&GO Project

Laude A, Ricci O, Bureau G, et al (2011) CO2 capture and storage from a bioethanol plant: Carbon and energy footprint and economic assessment. International Journal of Greenhouse Gas Control 5:1220–1231. https://doi.org/10.1016/j.ijggc.2011.06.004

Li B, Song Y, Hu Z (2013) Carbon Flow Tracing Method for Assessment of Demand Side Carbon Emissions Obligation. IEEE Transactions on Sustainable Energy 4:1100–1107. https://doi.org/10.1109/TSTE.2013.2268642

Luo X, Wang J, Dooner M, Clarke J (2015) Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy 137:511–536. https://doi.org/10.1016/j.apenergy.2014.09.081

Masoni P, Zamagni A (2011) Guidance Document for performing LCAs on Fuel Cells and H2 Technologies. Project deliverable for Fuel cell and Hydrogen-Joint Undertaking

McKenna RC, Bchini Q, Weinand JM, et al (2018) The future role of Power-to-Gas in the energy transition: Regional and local techno-economic analyses in Baden-Württemberg. Applied Energy 212:386–400. https://doi.org/10.1016/j.apenergy.2017.12.017

Messagie M, Mertens J, Oliveira L, et al (2014) The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment. Applied Energy 134:469–476. https://doi.org/10.1016/j.apenergy.2014.08.071

Meylan FD, Piguet F-P, Erkman S (2017) Power-to-gas through CO2 methanation: Assessment of the carbon balance regarding EU directives. Journal of Energy Storage 11:16–24. https://doi.org/10.1016/j.est.2016.12.005

Michalski J, Bünger U, Crotogino F, et al (2017) Hydrogen generation by electrolysis and storage in salt caverns: Potentials, economics and systems aspects with regard to the German energy transition. International Journal of Hydrogen Energy 42:13427–13443. https://doi.org/10.1016/j.ijhydene.2017.02.102

Moore J, Shabani B (2016) A Critical Study of Stationary Energy Storage Policies in Australia in an International Context: The Role of Hydrogen and Battery Technologies. Energies 9:674. https://doi.org/10.3390/en9090674

Müller LJ, Kätelhön A, Bringezu S, et al (2020) The carbon footprint of the carbon feedstock CO2. Energy Environ Sci. https://doi.org/10.1039/D0EE01530J

Parra D, Zhang X, Bauer C, Patel MK (2017) An integrated techno-economic and life cycle environmental assessment of power-to-gas systems. Applied Energy 193:440–454. https://doi.org/10.1016/j.apenergy.2017.02.063

Qu S, Liang S, Xu M (2017a) CO2 Emissions Embodied in Interprovincial Electricity Transmissions in China. Environ Sci Technol 51:10893–10902. https://doi.org/10.1021/acs.est.7b01814

Qu S, Wang H, Liang S, et al (2017b) A Quasi-Input-Output model to improve the estimation of emission factors for purchased electricity from interconnected grids. Applied Energy 200:249–259. https://doi.org/10.1016/j.apenergy.2017.05.046

Reiter G, Lindorfer J (2015) Global warming potential of hydrogen and methane production from renewable electricity via power-to-gas technology. Int J Life Cycle Assess 20:477–489. https://doi.org/10.1007/s11367-015-0848-0

Robinius M, Otto A, Syranidis K, et al (2017) Linking the Power and Transport Sectors—Part 2: Modeling a Sector Coupling Scenario for Germany. Energies 10:957. https://doi.org/10.3390/en10070957

Sadok R, Benveniste G, Wang L, et al (2020) Life cycle assessment of power-to-gas applications via co-electrolysis of CO2 and H2O. J Phys Energy 2:024006. https://doi.org/10.1088/2515-7655/ab72dd

Schemme S, Samsun RC, Peters R, Stolten D (2017) Power-to-fuel as a key to sustainable transport systems – An analysis of diesel fuels produced from CO2 and renewable electricity. Fuel 205:198–221. https://doi.org/10.1016/j.fuel.2017.05.061

Soimakallio S, Kiviluoma J, Saikku L (2011) The complexity and challenges of determining GHG (greenhouse gas) emissions from grid electricity consumption and conservation in LCA (life cycle assessment) – A methodological review. Energy 36:6705–6713. https://doi.org/10.1016/j.energy.2011.10.028

Sotos M (2015) GHG protocol scope 2 guidance. An amendment to the GHG Protocol Corporate Standard

Spath PL, Mann MK (2000) Life Cycle Assessment of Hydrogen Production via Natural Gas Steam Reforming

Spielmann M, Ruiz S, Zah R (2015) Analyse der Umwelt-Hotspots von Strombasierten Treibstoffen. Quantis Schweiz/Deutschland, Zurich

Steinmüller H, Reiter G, Tichler R, et al (2014) Power to Gas-eine Systemanalyse: Markt- und Technologiescouting und-analyse. Im Auftrag des BMWFJ

Sternberg A, Bardow A (2015) Power-to-What? – Environmental assessment of energy storage systems. Energy Environ Sci 8:389–400. https://doi.org/10.1039/C4EE03051F

Sternberg A, Bardow A (2016) Life Cycle Assessment of Power-to-Gas: Syngas vs Methane. ACS Sustainable Chem Eng 4:4156–4165. https://doi.org/10.1021/acssuschemeng.6b00644

Sternberg A, Teichgräber H, Voll P, Bardow A (2015) CO2 vs Biomass: Identification of Environmentally Beneficial Processes for Platform Chemicals from Renewable Carbon Sources. In: Gernaey KV, Huusom JK, Gani R (eds) Computer Aided Chemical Engineering. Elsevier, pp 1361–1366

STORE&GO (2020) STORE&GO. In: STORE&GO. https://www.storeandgo.info/. Accessed 18 May 2020

Suh S, Weidema B, Schmidt JH, Heijungs R (2010) Generalized Make and Use Framework for Allocation in Life Cycle Assessment. Journal of Industrial Ecology 14:335–353. https://doi.org/10.1111/j.1530-9290.2010.00235.x

Swiss Federal Customs Administration FCA (2017) Information on the Mineral Oil Tax Exemption for Biofuels in Switzerland.

https://www.ezv.admin.ch/dam/ezv/en/dokumente/abgaben/A%20MML/Min%C3%B6St/information-sheet-biofuels-in-switzerland.pdf.download.pdf/Information%20Sheet_Biofuels%20in%20Switzerland.pdf. Accessed 5 Jul 2020

Tranberg B, Corradi O, Lajoie B, et al (2019) Real-time carbon accounting method for the European electricity markets. Energy Strategy Reviews 26:100367. https://doi.org/10.1016/j.esr.2019.100367

Trost T, Sterner M, Jentsch M (2011) Mobility costs analysis and life cycle assessment of power-to-gas as alternative fuel. In: 6th International Renewable Energy Storage Conference

Tschiggerl K, Sledz C, Topic M (2018) Considering environmental impacts of energy storage technologies: A life cycle assessment of power-to-gas business models. Energy 160:1091–1100. https://doi.org/10.1016/j.energy.2018.07.105

Uusitalo V, Väisänen S, Inkeri E, Soukka R (2017) Potential for greenhouse gas emission reductions using surplus electricity in hydrogen, methane and methanol production via electrolysis. Energy Conversion and Management 134:125–134. https://doi.org/10.1016/j.enconman.2016.12.031

Varone A, Ferrari M (2015) Power to liquid and power to gas: An option for the German Energiewende. Renewable and Sustainable Energy Reviews 45:207–218. https://doi.org/10.1016/j.rser.2015.01.049

Vo TTQ, Rajendran K, Murphy JD (2018) Can power to methane systems be sustainable and can they improve the carbon intensity of renewable methane when used to upgrade biogas produced from grass and slurry? Applied Energy 228:1046–1056. https://doi.org/10.1016/j.apenergy.2018.06.139

Vo TTQ, Xia A, Wall DM, Murphy JD (2017) Use of surplus wind electricity in Ireland to produce compressed renewable gaseous transport fuel through biological power to gas systems. Renewable Energy 105:495–504. https://doi.org/10.1016/j.renene.2016.12.084

Vuarnoz D, Jusselme T (2018) Temporal variations in the primary energy use and greenhouse gas emissions of electricity provided by the Swiss grid. Energy 161:573–582. https://doi.org/10.1016/j.energy.2018.07.087

Weidema B (2000) Avoiding Co-Product Allocation in Life-Cycle Assessment. Journal of Industrial Ecology 4:11–33. https://doi.org/10.1162/108819800300106366

Weidema BP (2003) Market information in life cycle assessment

Wettstein S, Itten R, Stucki M (2018) Life Cycle Assessment of Renewable Methane for Transport and Mobility. Research Group for Life Cycle Assessment-Institute of Natural Resource …

Wettstein S, Stucki M (2017) Synthetic Power-to-Gas methane as fuel for transportation: life cycle environmental impacts of the PtG methane supply chain powered by renewable

electricity. In: Life Cycle Management (LCM) 2017, Luxembourg 3.-6. September 2017

Wiedmann T, Minx J (2008) A definition of ‘carbon footprint.’ Ecological economics research trends 1:1–11

Wokaun A, Wilhelm E (2011) Transition to Hydrogen: Pathways toward Clean Transportation. Cambridge University Press

Zhang X, Bauer C, Mutel CL, Volkart K (2017) Life Cycle Assessment of Power-to-Gas: Approaches, system variations and their environmental implications. Applied Energy 190:326–338. https://doi.org/10.1016/j.apenergy.2016.12.098

Zhang X, Witte J, Schildhauer T, Bauer C (2020) Life cycle assessment of power-to-gas with biogas as the carbon source. Sustainable Energy Fuels 4:1427–1436. https://doi.org/10.1039/C9SE00986H

AR4 Climate Change 2007: The Physical Science Basis — IPCC. https://www.ipcc.ch/report/ar4/wg1/. Accessed 14 Nov 2019a

AR5 Synthesis Report: Climate Change 2014 — IPCC. https://www.ipcc.ch/report/ar5/syr/. Accessed 6 Dec 2018b

ecoinvent. https://www.ecoinvent.org/. Accessed 11 Jun 2020c

5 Key findings and discussions

The key findings of different chapters in the thesis are summarized and discussed in this section in terms of the scientific and practice relevance for improving the regionalized effort in LCA development and applications, as well as the study limitation and potential future work and recommendations. Inevitably, some of the key take-away content are repeated from the discussion or conclusion sections of the previous individual chapters.

5.1 Scientific relevance of this thesis

Overall, the scientific relevance of the thesis are three folds: i) **Develop the model** to improve the process-based regionalized LCA for solving the cross-border commodity flow tracing between industries from different national jurisdictions in a matrix-based computational structure and **Identify the conditions** for a regionalized LCA model to yield accurate estimation of attributing the country of production origin of a focal product under study; ii) **Develop a practical guide to operationalize regionalized LCA** for a large-scale product portfolio of food products; iii) **Develop a systematic methodological framework** for evaluating the carbon footprint of Power-to-Gas to facilitate the process of applying and choosing different regionalized LCA models for electricity GHG intensity estimation and allocation method for CO_2 feedstock.

5.1.1 Definition and model formulation of regionalized LCA

Definition of regionalized LCA and key attributes. The understanding of "*regionalized LCA*" varies differently from the literature (Potting and Hauschild 1997, 2006; Mutel et al.,2009; Hellweg and Milà i Canals 2014; Reinhard et al. 2017; Yang, 2016, 2017; Patouillard et al. 2018). This thesis highlighted the importance of incorporating the traded-linked economic flows from the global supply chain perspective that map the country of production origin of a product to the country of consumption in a process-based regionalized life cycle inventory analysis and impact assessment. A process-based regionalized LCA analysis should include the following key components simultaneously: (i) *Regionalized unit process raw (UPR), (ii)*

Regionalized CFs, (iii) the cross-border commodity flow tracing of mapping the product origin of production to destination of consumption for a targeted product*, and (iv) regionalized LCA models for solving the* regionalized LCI analysis and applying the regionalized CFs of elementary flows. Last but not the least, it should also be compatible for the existing process-based LCA database, such as the ecoinvent that separate product domestic production and market datasets.

Regionalized LCA model development. When the country sourcing of a product is unknown, a variety of approaches are used for estimation, including but not limited to, the direct trade adjustment, global production or export average and network modeling. As there are no consensus on what approach should be taken, a process-based regionalized LCA analysis is often conducted arbitrarily depending on subjective choices. In this thesis, an integrated general regionalized LCA model is developed to better include the cross-border commodity flow tracing between industries from different national jurisdictions. Stemming from supply and use framework and building upon the production and market concept in the ecoinvent database, it solves the cross-border commodity flow tracing based on commodity balance for a given region directly in the regionalized LCA computational framework. The condition of achieving accurate estimation of sourcing countries in regionalized LCA are identified:

- A complete global value chain including all key trading countries for a product flow should be included to avoid potential truncation errors suffered by the conventional process-based LCA approaches.
- The production, trade, supply data of a product should be balanced for each country.
- Bilateral trade data should be used rather than using net trade (import or export) data.
- Avoid double counting: for example to avoid "certified product" counted twice for specific users and the average market supply to unspecified users

The production and trade data are often provided by conventional statistics, such as FAOSTAT for major crops and processed oils or ENTSO for electricity production, trade, and consumption information in Europe. It often involves certain debugging effort to reach mass balance and to deal with potential missing data situations.

Tests, validation and advantage of the model. Numerical example is used to demonstrate this model that shows the total production impact equals to the total impact occurred due to the final consumption activities, hence all flows are balanced, and the model is set up correctly.

- The numerical example (see Table 2.11 in Chapter 2) shows various potential pitfalls of regionalized LCA if they are not configured correctly:
    i) An incomplete inclusion of all trading partners could lead to an overestimate of 401% for consumption-based account and 133% for production-based accounting, compared to the benchmark value calculated with the developed model.
    ii) A global export share approach used to model product supply chain sourcing countries can give maximally 373% of impact of the benchmark "true" value calculated with the developed model. This is because different consuming countries source product differently from producing countries. This limitation has been discussed above for the Chaudhary et al. (2016) study.
    iii) The net consumption approach only yields 46% of impact for product 1 in region C compared with the "true value" that has the complete bilateral trade data calculated with the developed model.
- The Swiss palm oil trade data shows a large amount of palm oil are imported from Netherlands and Germany, but clearly these two countries are not the country cultivating palm oil. For this reason, the networking approach introduced in this thesis can simultaneously model the "true" country of production origin for each country of consumption directly in a regionalized LCA analysis. The advantage is demonstrated in a case study: when studying the biodiversity impact associated with palm oil consumed in Switzerland, Chaudhary et al. (2016) assumes 14% of palm oil are originally from United Republic of Tanzania based on the global export share approach, although the FAOSTAT reports only 0.2% of palm oil imported by Switzerland is from Tanzania and this study shows only 0.1% of palm oil imported by Switzerland is directly sourced from Tanzania. When FAOSTAT records Swiss import from Netherlands, but the actual sourcing country are Thailand, Indonesia, Malaysia, and Thailand, Papua New Guinea, and so forth. The proposed model captures the palm oil biodiversity impact from Papua New Guinea and Thailand hidden from the complex global value chain.

5.1.2 Operationalize the regionalized LCA for a large portfolio of food products.

The development of a stepwise framework. A stepwise framework is developed to guide each step of performing the regionalized LCA analysis. The feasibility and reliability is

validated by applying the proposed framework to conduct a regionalized LCA to assess and compare a large-scale portfolio of food product related to dietary choice. The stepwise framework follows a hierarchical and iterative process as listed below:

- define objectives, product systems, data quality requirement and spatiotemporal context for impact assessment and inventory analysis in the goal and scope.
- gather inventory data and perform data cleaning. In the case study, data was compiled for different product recipes, key ingredient sourcing countries, production factory locations, energy mixes, packaging designs, transportation, and end-of-life scenarios.
- perform gap assessment (completeness and consistency check) and prioritize key datasets to be regionalized; when primary data on key ingredient sourcing country of origin is not available or incomplete, trace commodity flows from production to consumption; key gaps for regionalized life cycle inventory data generation can be based on screening LCA results and data quality requirements defined in the goal and scope.
- generate spatially differentiated regionalized life cycle inventory data at the national level for key data gaps, for example for oilseeds in this study; when detailed spatial differentiation is challenging to obtain, spatial archetypes for LCI data can be developed instead, for example for dairy product in this study.
- generate and adapt spatially differentiated elementary flows, for example water flows in this study, to support regionalized impact assessment method if necessary.
- model climate change impacts form land use change (LUC) for key agricultural ingredients when LUC is non-negligible to ignore.
- perform uncertainty analysis and sensitivity analysis related to choices of model and data, for example, the choice of functional unit, allocation method, supply chain sourcing variability and the worst-supply chain scenario analysis, land use change GHG emission method and so forth.
- the steps above are inherently iterative, until valid conclusions can be drawn according to the predefined data quality requirement.

Further details for a robust regionalized LCA analysis for food product are discussed below:

- **Prioritize the effort for developing country-specific LCI data.** The spatially differentiated LCI data that are missing or lacking sufficient data quality can be identified through contribution analysis, sensitivity analysis and pre-defined data

quality requirement. When detailed spatial differentiation is challenging to obtain, spatial archetypes can be developed for LCI as in the case for dairy product systems.

- **Consider country-specific Land use GHG emissions for agricultural commodities.** Different LUC GHG emission models are available, and the LUC modeling is highly uncertain. The estimation could vary largely depending on discounting approach (linear or equal discount of the impact over 20 years), allocation of impacts to crops for a given region (based on areas of increase or current area occupation), and scope of analysis (for example if peat degradation is considered or not). The results of LUC GHG emissions should be interpreted with caution. When certification programs is considered, it is important to make a differentiation between a deforestation-free claim and zero GHG emissions from the land use change, for two main reasons: 1) the scope of land use change is beyond deforestation per se. Any type of land type conversion can be considered as land use change, implying potential change of carbon in the soil and vegetation; ii) the LUC impact quantification takes 20 years' time horizon, a today's deforestation-free agricultural ingredient might still bear legacy emission impact.
- **Simplified regionalized LCA model considering product sourcing locations**. A simplified regionalized LCA model is used in this case study to study the commodity flow sourcing modeling are independent from the rest of LCA modeling. At the time of conducting this work, the understanding of network trade modeling as developed in this thesis and its application into regionalized LCA is yet mature. For the current work, a tiered supply chain modeling approximation based on FAOSTAT production and trade statistics is used instead for the commodity flow sourcing estimation. The tiered approach traces back to trading partners more than one tier, in this case up to 2-3 tiers of supply chain. The approach has limitation of potentially attributing the wrong country of sourcing origin, as illustrated in the case of Chaudhary et al. (2016), therefore a worst-case supply chain sourcing analysis is used to examine if the conclusion is still valid. By using the networking modeling approach introduced in chapter 2 of the thesis, the reliability of regionalized LCA results can be further improved.
- **Uncertainty and variability**. Uncertainty can also arise due to parameter uncertainties and due to choices of data or modeling approaches. The parameter uncertainty can be characterized by pedigree score and analyzed with either analytical uncertainty

propagation or monte Carlo simulation. Uncertainty due to choices can be addressed by various sensitivity analyses, as performed in this study. Natural variability, for example, the product recipe formulation for spread can be different for consumer markets, could only be assessed by including these inter-product variabilities into assessment and they cannot be reduced by uncertainty assessment.

5.1.3 Methodological framework to assess the carbon footprint of PtG

We developed a systematic methodological framework for evaluating the carbon footprint of PtG is developed to facilitate the process of choosing different regionalized LCA models for electricity GHG intensity estimation and allocation method for CO_2 feedstock. In relation to the regionalized LCA topic, the key insights are formulated below:

- **Grid mix modeling choices.** Although the modeling of electricity carbon footprint has been increasing taking a regionalized LCA approach, there are different model choice and assumptions to be made, notably including the average or residual production vs consumption perspective in a region and yearly or hourly/seasonal temporal resolution. We show when a country's grid mix is more decarbonized, for example in Switzerland, the comparative advantage of SNG from PtG becomes sensitive to the choices of electricity modeling approaches whether cross-border trade and residual mix (excluding certified renewable electricity) are considered. A decision framework is developed in this research to guide the choice of modeling choices based on the rule of ISO/TS 14067(2013) and EU Product Environmental Footprint Category Rules guidance (European Commission 2018). However, it is important to recognize that the GHG protocol scope 2 guidance (Sotos et al. 2015) requires the combustion emission of purchased electricity based on production mix of a region, instead of the consumption mix recommended in this research. And Brander et al. (2018) criticized the recommended market-based method for reporting purchased electricity emission factor with GOO for renewable electricity as "creative accounting". With divergent opinions from different guidance and literature, we argue the choice of regionalized modeling of electricity emission factor should be further investigated and standardized when designing policies related to the GHG calculation for PtG as low-carbon fuels.
- **Temporal resolution**. Even if the yearly average modeling shows a lower carbon footprint for the PtG production compared to fossil natural gas in a PtG scenario in Switzerland, we show that more than 50% of time over the year the production of PtG

production could lead to a higher carbon footprint. Thus, the practical deployment of PtG production should be guided in a finer, such as hourly, temporal resolution.

5.2 Practical relevance of the thesis

5.2.1 Improving the LCA database and regionalized LCA case study

Agricultural regionalized LCA Database. The analysis and comparison performed in this work shows the importance of carefully considering the product supply chain sourcing estimation when the primary data is not available. Arbitrary choices of supply chain sourcing estimation approach or incomplete inclusion of trading partners could lead to erroneous estimation of regionalized LCA results. As shown in Figure 5.1, the approach developed in this study can be easily applied to fill in the gaps of missing global value chain for spatially differentiated agricultural and food LCI database development, such as WFLDB, AGRIBALYSE, ecoinvent and other regionalized LCA studies. As illustrated in the first case study of estimating the biodiversity loss from palm oil consumption in Switzerland, the approach introduced in this study can potentially reduce the model uncertainties associated with supply chain sourcing estimation introduced by arbitrary assumptions.

Differentiation of certified vs residual mix. There are rising demands for "certified" product, such as certified palm oil and certified electricity. With the model proposed in this thesis, the certified and residual production or consumption mix can be better estimated.

The choice of regionalized LCA modeling approach towards practical application. The case studies illustrated in this thesis shows that there is no single correct way to perform regionalized LCA. The use of regionalization LCA depends on study context, data availability, time effort and resources.

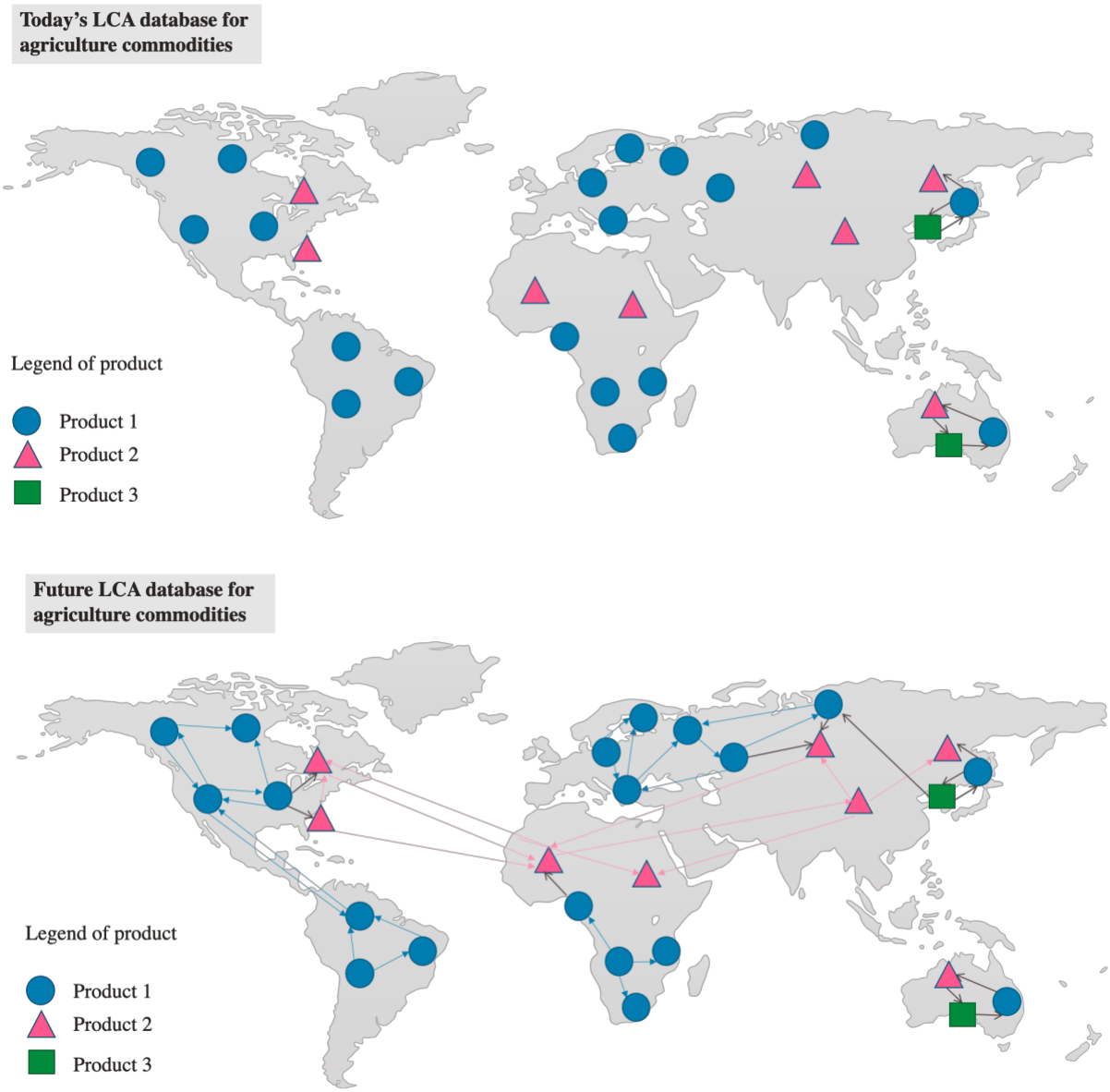

Figure 5.1 Relationship of producers and consumers described by the current and future regionalized LCA database for agricultural commodities

5.2.2 Product environmental footprint labeling and comparison

Many large cap companies in the food industry are setting up emission reduction and roll out environmental footprint labeling initiatives but doubting if it is possible to streamline the assessment of large portfolio of product with complex multi-tier sourcing supply chain and high spatial variability of agricultural commodities. In this thesis, we provide a practical recipe (framework, approach, and examples) of how this can be done and demonstrate that this is feasible and reliable with reasonable time effort. The inter-product variability of environmental footprint and associated uncertainties are assessed with the regionalized LCA. The hotspots for mitigation are illustrated. Building on the work from the study, Upfield starts rolling out the

carbon footprint labeling on 100 million packs by end of 2021 to encourage consumers to make more sustainable food choices, as show in Figure 5.2

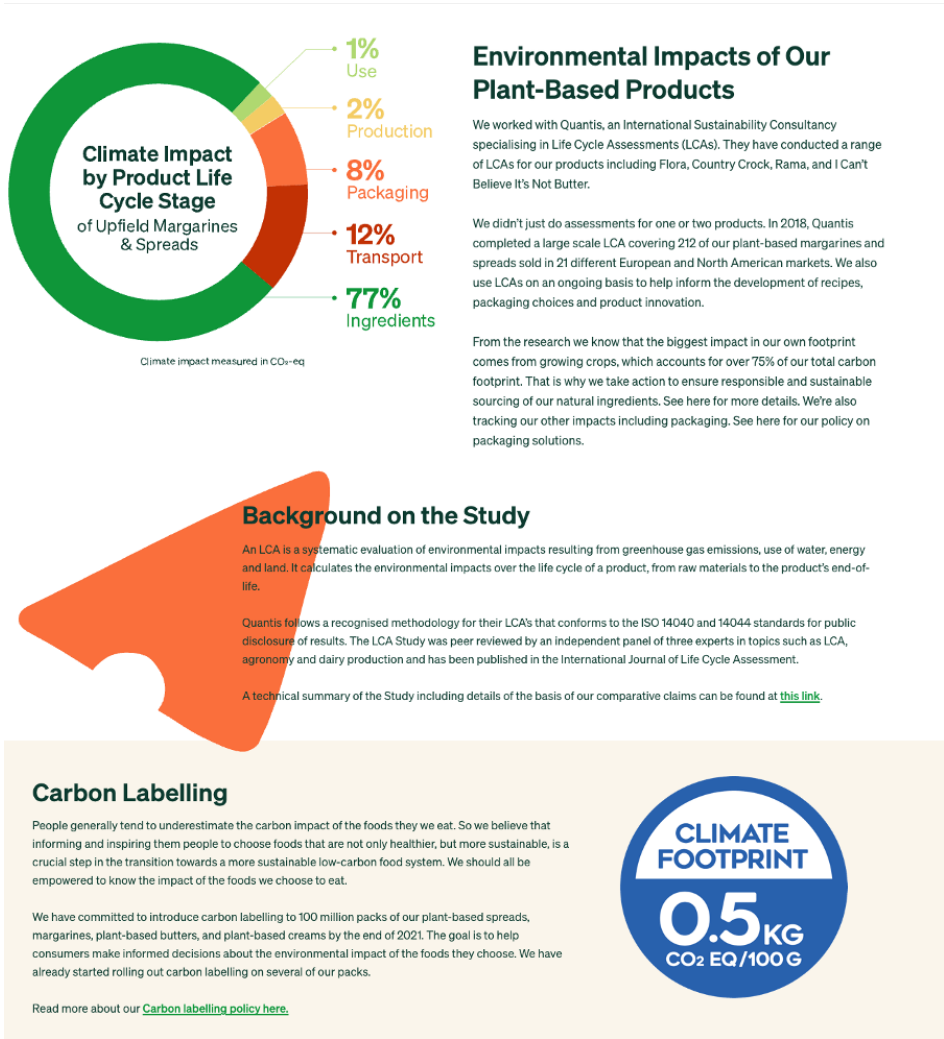

Figure 5.2 Example of environmental footprint communication and carbon labeling

5.2.3 Inform policy making for Power to Gas technology development

Key insights. Our study shows that the climate advantage of SNG produced from PtG over fossil natural gas will not exist if the use of the carbon molecular from the CO_2 feedstock to produce SNG bears the full climate burdens for the final release of CO_2 emissions, regardless of technology choices, electricity input types, and regionalized LCA modeling choices. The analyses find the essential condition for SNG to have a lower carbon footprint than fossil natural gas is by mainly powered by supplier-specific renewable electricity mix with guarantee of origin. The regionalized LCA analysis for grid electricity-derived fuel should consider temporal variations of electricity consumption on an hourly basis beyond using a yearly average estimation. Towards the reliability of assessing the PtG carbon footprint and better

policy design for incentivizing low-carbon fuel development, we make the following recommendations as the minimum criteria to follow:

- **Emission factor limit of electricity input**. The estimated maximum threshold of GHG intensity of electricity input is 86-155 g CO2-eq/kWh to be lower than fossil natural gas when CO_2 feedstock are taken from the ambient air or from those otherwise would be released into atmosphere. However, these values are sensitive to choices of the carbon footprint of fossil counterparts. Renewable electricity with a guarantee of origin or low-carbon grid power could meet this threshold. The temporal variability of electricity supply should be considered for regionalized LCA analysis.
- **A holistic system perspective.** We recommend the accounting of the impact of CO_2 feedstock and its application should take a systematic view to consider the heat integration and valorizations opportunities provided by external low-carbon heat sources or the surplus heat from electrolyzer and methanation processes, as demonstrated in this study.

Detailed carbon footprint of the pilot PtG plants. Overall, SNG produced from PtG demonstration sites ranges from 22.4-43.5g CO_2-eq/MJ SNG with different types of renewable electricity, less than that from fossil natural gas (63.7 g CO_2-eq/MJ Natural gas, with 10.4 CO_2-eq/MJ from natural gas production and 53.3 CO_2-eq/MJ from combustion). The main variations of different PtG scenarios come from the consideration of heat valorization, energy efficiency of electrolyzers, and options of CO_2 capture. These results assume that the release of CO_2 of SNG combustion do not bear burdens, hence the 53.3 CO_2-eq/MJ from combustion is avoided, because CO_2 feedstock is captured from ambient air or those otherwise would be released to air.

- **Electricity input** for electrolysis is the largest contributor of the carbon footprint (22.7-31.5 g CO_2-eq/MJ-SNG), while **valorizing excess heat** provides the largest credit, ranging from replacing natural gas boilers (17.6 g CO_2-eq/MJ-SNG) or replacing heat pump (8.4 g CO_2-eq/MJ-SNG). Electricity for methanation and other processes contribute to 1.1- 4.2 g CO_2-eq/MJ-SNG, depending on technology choices. The Honeycomb catalytic reactor deployed in Falkenhagen has the largest impact, 4.2 g CO_2-eq/MJ SNG; however, it also provides the largest credit by valorizing excess heat. Thus, a holistic systematic view is needed to understand the optimal choice of technology in different locations.

- **Equipment.** Based on the data collection from the actual three pilot PtG plants, we provide the first accurate estimation for equipment and balance of plant of building the PtG plants. Our estimates show the carbon footprint ranges from 5.7-8.8 g CO_2-eq/MJ SNG. The main equipment and consumable materials, including electrolyzer, reactor and catalyst consumption, only contribute to 1.7-1.9 g CO_2-eq/MJ SNG. Majority impact comes from auxiliary system, such as liquid and gas treatment systems, CO_2 tank storage and conditioning unit, heat management module and process center modules. With the improvement of the economy of scale, the auxiliary impact might be reduced largely.
- **CO_2 feedstock.** We report the carbon footprint of CO_2 feedstock supply ranges from 0.1 g to 7.3 g CO_2-eq/MJ for capturing, and transportation, compressing CO_2 when renewable electricity is used depending on sourcing scenarios. If the electricity carbon intensity is based on the current national grid, the carbon footprint of the CO_2 feedstock supply would be much higher. The CO_2 capture and supply from the wastewater treatment plant in Solothurn, Switzerland contributes to a negligible impact of 0.1 g CO_2-eq/MJ SNG, because (i) the biological methanation reactor can tolerate CO_2 with less purity, reducing the requirement of CO_2 upgrading and purification and (ii) the proximity of the wastewater plant supplying the CO_2. For Falkenhegan Germany, the liquefaction and transportation of 400 km of the CO_2 feedstock from the bioethanol plant contribute to 7.3 g CO_2-eq/MJ SNG. The *in-situ* CO_2 by direct air capture (DAC) contributes to 7 g CO_2-eq/MJ SNG, whereby 60% comes from renewable energy consumption related to CO_2 capture, and 40% are related to the DAC equipment.

5.3 Study limitations

Currently the regionalized LCA with tiered supply chain approximation is used for the regionalized LCA calculation in Chapter 3 comparing dietary choice, in conjunction with the worst supply chain scenario analysis. However, the swiss palm oil biodiversity assessment example demonstrated in Chapter 2 can also be applied for all agricultural commodity assessment in this chapter 3 to obtain more accurate baseline environmental footprint. In chapter 2, I describe the regionalized LCA model can and should differentiate contractual relationship that creates direct link between suppliers and consumers and residual market pool data. The importance of this type of differentiation is shown in Chapter 4 Power to Gas comparing residual consumption mix and generic national average consumption mix of

electricity used for PtG production, although the European residual mix calculation provided by the Association of Issuing Bodies (2019) Residual Mixes does not follow strictly the approach introduced in Chapter 2 of this thesis. To set up this type of model, the commodity flow production, trade and consumption data with a contractual relationship (e.g., certified electricity and agricultural commodities) and the rest of commodities should be separated and balanced on a regional level when building the global regionalized life cycle inventory database for a specific commodity (electricity or agricultural product). With a similar challenge facing the inter-regional input-output model (IRIO) from the regional input-out economics, in practice, this type of model is rarely developed because of lack of data. However, with the capacity of tracing the flow of commodity being improved, it might become possible in the future.

All the regionalized LCA analysis performed in this study are still on the country-level, relying on either statistics or supplier-specific data. This is quite common for the current LCA database and applications in the industry. The information yields through the regionalized LCA on the country level or sub-nation regional level are sufficient to answer many strategical questions as asked in this thesis and to identify key hotspots for further development. However, there are also a few clear drawbacks:

- This study does not address the potential errors or uncertainties embedded in the national statistics, trade statistics such as FAOSTAT. For example, the land use change GHG data and supply chain sourcing data estimation are highly dependent on the data quality reported by FAOSTAT. For the ENTSO-e statistics, only net trade data is available for this thesis, although ideally bilateral trade data is required.
- This study does not address the model or data source uncertainties of spatial agricultural LCI data. Different data sources might provide inconsistent estimation. For example for irrigation water use for the same type of crop for a given location, Pfister et al. (2009) and Water footprint Network (Hoekstra et al. 2014) might disagree with each other.
- The model developed in Chapter 2 of this thesis aims to provide a better estimation of regionalized LCA results especially when supplier specific information is unknow. However, without the supplier-specific information, the regionalized LCA results often cannot reflect the intra-national variabilities or site-specific (e.g., a specific farm)'s environmental performance of purchased product, as trade statistics is mainly on the country level. For companies looking for tracking their environmental performance

over years, acquiring site-specific data by working directly with their suppliers (for example farmers) might be needed in the future.

5.4 Future work and recommendations

The key future work and recommendations are summarized in **Figure** 5.3.

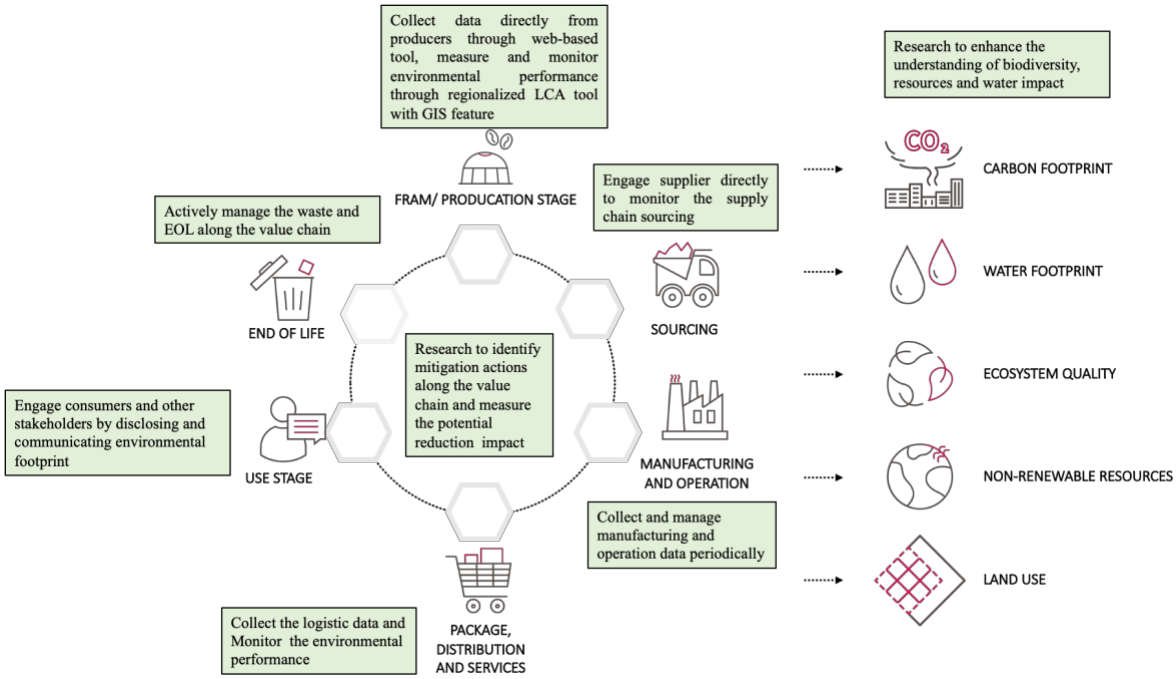

Figure 5.3 Towards the increased data accuracy for regionalized LCA

Actions for database providers

- Prioritize the regionalization effort to increase the coverage of the global value chain and level of details for spatial differentiations
- Include the global supply chain relationship for agricultural commodities in WFLDB or ecoinvent as illustrated in **Figure** 5.1

Actions for researchers

- Increase the reliability of spatial information from the producers, such as the average water use for different crops, as well as the region-specific land use change data
- Increase the bilateral trade data and temporal resolution when modeling the electricity market with complete trading partners
- Increase spatial resolution of LCI data from country level to sub-national level or grid-cell level for agricultural commodities

- Differentiated the certified vs residual production and consumption mix for key agricultural commodities and electricity product

Actions for companies

- Building the capacity of tracking its own supply chain product sourcing information
- Building the tool and capacity of assessing supplier-specific emission factors
- Set up roadmap for emission reduction actions, and measure the potential benefits

Action for LCA software service providers

- Building the capacity of linking data acquisition tools to life cycle impact calculation tools to streamline the data collection and analysis effort
- Building the capacity of processing data with higher spatiotemporal resolutions (hourly and sub-national /grid-cell level) within the matrix-based regionalized LCA computational framework

6 Conclusions

This chapter provides the concluding remarks of the main contribution, outcome and take-away message derived from this thesis from respective chapters. They are formulated around the three core questions raised in the research objectives.

Question in the objective 1: How to improve the process-based regionalized LCA to solve the cross-border commodity flow tracing between industries from different national jurisdictions?

Answer: **Regionalized LCA model development**. When the sourcing country of production origin for a purchased product is unknown, a process-based regionalized LCA analysis is often conducted arbitrarily depending on subjective choices of estimating sourcing countries of production origins, for example, using the direct trade adjustment and global production or export average, as commonly applied in the existing LCA database and studies. Stemming from the supply and use concept and the network modeling concept, a general matrix-based computational structure is developed for process-based regionalized LCA to improve the inclusion of spatial details of tracing the spatial locations of cross-border product flows along supply chains from production to consumption. It is based on the commodity balancing of a product on the country level with production, consumption and bilateral trade data. The model is validated with a numerical example and demonstrated with a case study from literature for an improved accuracy of impact results. Several aforementioned predominant assumptions used in process-based regionalized LCAs for deriving spatial location information are examined and compared with numerical examples, showing the large variabilities of impact results and potential over- or under-estimation of impact results using global production share, global export share, direct trade adjustment, and net import data, and so forth. The proposed model offers a coherent and transparent way of analyzing the influence from different trade assumptions or incomplete inclusion of trade data and supply chain activities in a process-based regionalized LCA analysis. It can be used to reduce the uncertainties associated with

supply chain sourcing estimation in a case study introduced by arbitrary assumptions. The approach developed in this thesis is compatible with the existing ecoinvent database with a matrix-based computational algorithm, enabling an efficient calculation. It can be easily applied to fill in the gaps of missing global value chain for spatially differentiated agricultural and food LCI database development, such as WFLDB, AGRIBALYSE, ecoinvent and for general regionalized LCA case studies.

Question in the objective 2: How practical and reliable is to apply regionalized LCA approaches to perform large-scale dietary comparison and evaluate if the climate advantage hypothesis of plant-based fat spreads over dairy butter holds regardless of the variabilities of product recipes, geographies, and the influence of inclusion of GHG emissions from LUC, and without shifting climate impacts to water and land use?

Answer: **Operationalization of the regionalized LCA.** A stepwise framework for assessing a large-scale portfolio of food product was developed to operationalize the application of regionalized LCA. The key steps consists of an iterative process of estimating missing sourcing country information, performing gap assessment (completeness and consistency check) prioritizing and generating missing country-specific spatial (archetype) LCI datasets, modeling country-specific GHG emissions from land use change (LUC) for agricultural commodities, and analyzing uncertainties associated with parameters and model choices (for example different Land Use Change GHG emission allocation model) and data assumptions (for example the supply chain sourcing variabilities and functional unit choice).

The feasibility and reliability are tested and validated with a case study for comparing the environmental impacts of 212 plant-based fat spreads and 40 dairy butter sold in 21 countries. This study confirmed that plant-based spreads had lower climate, water and land impacts than butter, despite variability of product recipes, geographies and influence of LUC. This study confirmed that plant-based spreads had lower climate, water and land impacts than butter, while large variabilities exit across products, ranging from 0.98 to 6.93 (mean 3.3) kg CO_2-eq/kg for 212 plant-based spreads and 8.08 to 16.93 (mean 12.1) kg CO_2-eq for 21 dairy butter with 95th confidence interval. It identifies the main drivers of GHG emissions for plant-based products are oilseed cultivation and the associated LUC emissions, which can vary significantly depending on type of oilseeds and quantity. Thus, the inclusion of accurate land use change modeling for agricultural product is one of the key factors for enabling the reliable

regionalized LCA analysis. With the high spatial variabilities of LUC impact of agricultural product, the reliability of regionalized LCA analysis on a single product level are highly dependent on the assumptions of the sourcing country of production origins. Therefore, it becomes essential to ensure a reliable estimation of tracing the commodity flow of the agricultural product from the country of production origins to country of consumption for regionalized LCA analysis of agricultural commodities and derived product. Ideally, commodity sourcing spatial location information should be tracked and provided by suppliers to yield accurate estimation. When that is not possible, the method proposed in chapter 2 can be leveraged to further improve the accuracy of tracing commodity flow and subsequently improving the estimated environmental footprint results for each individual product. Overall, this research offers a framework for performing regionalized agricultural LCA for a large portfolio of products thereby enabling identification of inter-product variabilities and hotspots for the development of mitigation strategies. Key mitigation opportunities include reducing oilseed ingredients' embodied impacts by optimizing product recipe design and adapting supply chain sourcing and agricultural practice.

When industries are moving towards emission reduction and target setting, supplier-specific and field-level farm data would become increasingly important. Regionalized LCA analysis on the national or regional level can effectively help prioritize the effort and hotspot of actions during this process. Key practical impact of this work is that the approach introduced in this thesis is now being leveraged by a food company to roll out the carbon footprint labeling on 100 million packs to inform consumers' purchase decision-makings on dietary choice.

Question in the objective 3: What is the influence of regionalized LCA model choices and spatiotemporal variability of electricity input and the allocation of CO_2 feedstock on the PtG carbon footprint?

Answer: A systematic methodological framework is developed in this thesis to facilitate the process of applying and choosing different regionalized LCA models for electricity GHG intensity estimation and the allocation and accounting of CO_2 feedstock impact. By applying this framework to three representative PtG demonstrate plants, the following insights are drawn:

Influence of regionalized grid mix modeling choice and spatiotemporal variability on the PtG carbon footprint. With regionalized LCA approaches, electricity emission factors be calculated based on "location-based approaches" from a territorial production-based vs

consumption-based perspective without differentiating specific users in a given region, or based on "market-based approach", differentiating different users based on the contractual relationship, such as the guarantees of origins (GOO) and residual mix excluding GOO for unspecific user in a region for different (yearly or hourly/seasonal) temporal resolutions. We show the comparative advantage of SNG from PtG is sensitive to the choices of electricity modeling approaches depending on how electricity cross-border trade and residual mix (excluding certified renewable electricity) are considered, especially when a country's grid mix is more decarbonized, for example in Switzerland. When the electricity input is based on a renewable electricity mix with guarantee of origin, PtG production systems under study have a 32-65% reduction of carbon footprint compared to the fossil natural gas. Thus, one fo the essential condition for SNG to have a lower carbon footprint than fossil natural gas is by mainly powered by supplier-specific renewable electricity mix with guarantee of origin.

All PtG production systems in this study do not show climate benefit against fossil natural gas when using the grid modeling based on the residual consumption mix from the selected countries. Based on the model assumption of the national territorial average consumption mix on a yearly basis, it shows PtG production in Switzerland could be operated to provide climate benefits. When moving from yearly average temporal resolution to hourly resolution, in the above scenario, we show that more than 50% of time over the year the production of PtG production in Switzerland could lead to a higher carbon footprint. Thus, the practical deployment of PtG production should be guided in a finer temporal resolution to gain potential climate benefits. A decision framework is developed in this research to guide the choice of modeling choices based on the rule of ISO/TS 14067(2013) and EU Product Environmental Footprint Category Rules guidance (European Commission 2018). We recommend further harmonization and standardization of the choice and approach of modeling the electricity carbon intensity used for PtG is needed.

Influence of CO_2 feedstock allocation and accounting. Our study shows that the climate advantage of SNG produced from PtG over fossil natural gas will not exist if the use of the carbon molecular from the CO_2 feedstock to produce SNG is not carbon neutral without consideration and separation and supply impact from a cradle to grave perspective, regardless of technology choices, electricity input types, and regionalized LCA modeling choices. Thus, a correct accounting of CO_2 feedstock is vitally important for the evaluation of carbon footprint of PtG, yet the proper climate accounting of CO_2 feedstock used for PtG remain a challenge,

as CO_2 can be either treated as an elementary flow or as an economic flow. We identified the key issues are related to the debate on if CO_2 sourcing from fossil origin can be used for PtG, how impact of CO2 feedstock should be allocated and the accounting system boundary (cradle to gate vs cradle to grave). **(i) Reference condition and criteria for CO_2 sourcing selection**. Our analyses show the importance of clarifying the reference condition or status quo of the CO_2 sources, whether direct release to atmosphere (non-competitive use) or competitive use. Most studies assume the current CO_2 sources are directly releases to atmosphere without capture. With that reference condition, the carbon footprint results of the Solothurn PtG case study converge to the same value regardless of how the recommended allocation approach is called, from substitution (Muller et al. 2020), subdivision (this study), system expansion (Zhang et al. 2017), comparative approach (von der Assen et al. 2016) to carbon neutral (Reiter et al. 2015). The underlying reasoning for this is because they all use the same reference condition or assumption of the current status quo. We recommend the preferable allocation approach is subdivision or system expansion /substitution, and they generate the same cradle to grave impact results when the reference condition is the direct release into atmosphere or other non-competitive use of CO_2 sources. We recommend this reference condition as the key criteria for CO_2 sourcing selection. **(ii) Non-discrimination of CO_2 from fossil sourcing origin.** On this basis, we recommend the development of PtG projects should not rule out the CO_2 sources from traditional fossil origins, such as refineries and cement, and chemical industries if it meets the CO_2 sourcing criteria mentioned above to avoid resulting into suboptimal outcome. **(iii) Cradle to grave and systematic perspective**. To avoid the contentious debate of negative credits from a cradle to gate perspective and "carbon neutral" for the CO_2 sequestered in the intermediate product, the system boundary for PtG applications is recommended to include the impact of the final oxidation of SNG even if the exact targeted utilization (storage, transport or heating sources) is not defined. Furthermore, we recommend the accounting of the impact of CO_2 feedstock and its application should taking a systematic view to consider the heat integration and valorization opportunities provided by external low-carbon heat sources or the surplus heat from electrolyzer and methanation processes, as demonstrated in this study.

In conclude. There is no one size fitting all when it comes to the configuration of regionalized LCA model and approach when dealing with different applications. The regionalized LCA model and methodology with case studies illustration developed in this study contribute to

advance our understanding in the methodological aspect of regionalized LCA model and key issues related to practical operationalization and applications. Future work should focus on prioritizing the regionalization effort to include the global supply chain structure and better differentiation of supplier-specific data and residual mix as well as temporal differentiation of the process-based LCA database to facilitate a more robust adoption of regionalized LCA.

Annex

Annex for Chapter 3 Supporting information for spread and dairy modeling

S3.1 Terminology

Detailed terminology for plant-based and dairy-based products are defined as follows:

- PB spreads: Plant-based fat spreads are spreadable or fluid emulsions, made principally of water and edible fats and oils. Milk fat content is no more than 3% of the total fat content for almost, except the 27 blended spreads (maximum 30% milk fat of the total fat content) (Upfield's own definition).
- Dairy spread: Dairy fat spreads are milk products relatively rich in fat in the form of a spreadable emulsion principally of the type of water-in-milk fat that remains in solid phase at a temperature of 20°C. The milk fat content shall be no less than 10% and less than 80% and shall represent at least 2/3 of the dry matter. (FAO and WHO, 2011)
- Butter: Butter is a fatty product derived exclusively from milk and/or products obtained from milk, principally in the form of an emulsion of the type water-in-oil. The milk fat content shall be no less than 80%, the water content no more than 16% and the milk solids-not-fat content no more than 2%. (FAO and WHO, 2011)
- PB creams: Plant-based creams are creams in which the milk fat is replaced by plant-based fats. (Upfield own definition)
- Dairy cream: Cream is the fluid milk product comparatively rich in fat, in the form of an emulsion of fat-in-skimmed milk, obtained by physical separation from milk. The milk fat content shall be no less than 10%. (FAO and WHO, 2011)

One or several recipes of PB spreads, including blended fat spreads and PB creams are assessed for each market. PB spreads and are compared to average, butter produced and sold in the same market. PB creams are compared to average dairy cream (30% fat) produced and sold in the same market. Denmark, Finland and Sweden are special cases, where the following alternatives to PB spreads and PB creams are considered:

- Denmark: Butter, dairy spread (75% fat)
- Finland: Butter, dairy spreads (75% fat, 60% fat and 40% fat), dairy creams (40% fat, 27% fat and 15% fat, lactose-free vanilla whip coconut fat-based and lactose-free vanilla whip palm kernel fat-based)
- Sweden: Butter, dairy spreads (75% fat, 60% fat and 40% fat), dairy creams (40% fat, 27% fat and 15% fat and cream-based vanilla whip)

In many cases, different products (i.e., sold under different brands and in different packaging in different markets) have the exact same recipe. Overall, a total of 228 PB spreads/creams with different fat levels and types of packaging are corresponding to 126 different recipes. “Average” butters, dairy spreads and creams aim to be representative of typical products sold in each market and serve as benchmarks for Upfield recipes sold in the same market. These products use as their main ingredient an average raw milk for each country and consider an average technology for processing into butter and cream respectively.

S3.2 Detailed method description

This section is the supporting information for Section 3.2 methodology of the thesis.

1) Define relevant **data quality requirements** and **collect** the primary raw data related to the bill of activities, including sourcing locations for all product ingredients and recipes sold in all 21 consumer markets. In this study, the spatial context for data collection is on a country level.
2) **Data cleaning**: organize, clean and harmonize the collected primary data and secondary data ready for further data analysis. In this study, we use R software together with Excel tool to perform this task.
3) Perform **gap assessment and prioritization** through various exploratory techniques, such as contribution analysis, variability and sensitivity analysis, uncertainty analysis or scenario analysis.
4) When primary data on key ingredient sourcing country of origin is not available or incomplete**, trace** commodity flows from production to consumption based on secondary statistic data for national production, consumption and bilateral trade data for a given commodity together with associated existing primary information provided by an organization.
5) Identify and prioritize **key data gaps** for regionalized life cycle inventory data generation based on screening LCA results and data quality requirements defined in the goal and scope; in this case this refers to low-quality or missing data for vegetable oil ingredients and dairy products for different sourcing countries of origins. The available spatial agricultural LCI data, based on several data sources, such as World Food Life Cycle Database (WFLDB) (Peano et al. 2012) (Nemecek et al. 2015), Agri-footprint 2.0 (Durlinger et al. 2014) and the ecoinvent v3.3 database. The data quality of these data sets are assessed based on the pedigree matrix approach (Weidema et al. 2013). Given the complexity for regionalization of all data points, prioritization of data gaps is also essential. The step of gap identification and prioritization in this research conforms to the latest recommendation from the regionalized LCIA working group under the UNEP/SETAC Life Cycle Initiative, calling for prioritization of developing regionalized inventories and assessment (Mutel et al. 2018).
6) Auto-generate **regionalized** life cycle inventory data at the national level for key missing data with the Agricultural Life Cycle Inventory Generator (ALCIG) (Quantis 2016), a tool consistent with the WFLDB approach for modeling the life cycle inventory of

agricultural products (Nemecek et al. 2015). When detailed spatial differentiation is challenging to obtain, **spatial archetypes**, for LCI data are developed instead, for example for dairy farm systems. See more discussions on spatial archetype below. This practice is consistent with the recommendation given by Mutel et al (2018) and Kounina et al (2018) which promotes combining sector-specific archetypes with spatial information as an efficient way to tackle the challenge of missing data.

7) Generate and adapt **spatially differentiated water related elementary flows** to perform a regionalized water scarcity footprint assessment based on the AWARE approach. The assessment of the water scarcity footprint indicator requires particular attention to the consistent modeling of all life cycle inventory data, both in the foreground and background systems. In the present study, all foreground and background inventory data were adapted as to ensure the following: Water flows in every process were properly balanced, which enabled to calculate the amount of water consumed as the difference between inputs and outputs. Water flows were all regionalized at country-level as per the location where the withdrawals (inputs) and releases (outputs) were taking place, therefore enabling the association to the appropriate characterization factor.
8) Model **climate change impacts from land use change (LUC)** for key agricultural ingredients of all markets in a consistent way.
9) Perform **uncertainty and sensitivity analyses** to assess the robustness of results due to data quality, modeling choices and assumptions.
10) The steps above are inherently iterative, until valid conclusions can be drawn according to the predefined data quality requirement.

Spatial archetypes of dairy systems

This section is the supporting information for Section 3.2.4 of the thesis.

Detailed spatial differentiation is challenging to obtain for dairy systems in all countries, thus a spatial archetype approach is developed in this study. The overall modeling framework for building country-average spatial archetype of dairy milk datasets is illustrated in the Fig. S2-1 below. It requires firstly develop "archetype" - typical farms and different manure management system (MMS); and secondly combine these archetypes with national mix of different proportion of archetypes to obtain spatial archetype life cycle inventory for dairy milk of different countries. In addition, mechanized or non-mechanized farm management activities are also modelled as per the WFLDB (Nemecek et al. 2015).

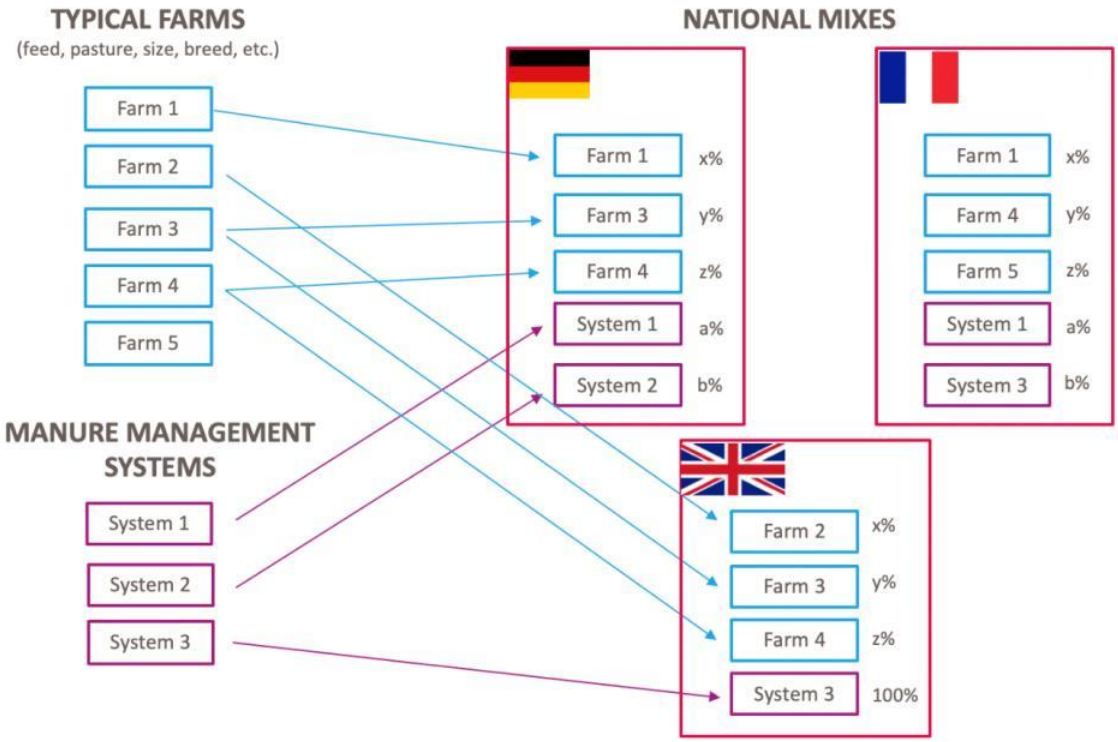

Fig. S2-1. Spatial archetype of dairy LCI modeling

Characterization of dairy farm archetypes

23 farm archetypes, describing how cows/cattle are fed and held at the farm, are modeled, based on the IFCN "typical farms", characterized in a global study on dairy systems from The Food and Agriculture Organization of the United Nations (FAO), the International Dairy Federation (IDF) and the IFCN Dairy Research Network (FAO, IDF, IFCN 2014). Additional reference studies are also used for specific countries, such as the "Greenhouse Gas Emissions from Production of Fluid Milk in the US" (Thoma at al. 2013) for the U.S. and the

"Environmental and Socioeconomic Life Cycle Assessment of Canadian Milk" (DFC 2012) for Canada, both conducted at national scale with high-quality primary data. The herd structure and milk production for different dairy farm archetypes are available in the Table S2-1. Daily feed intake of lactating cows for dairy farm archetypes is given in Table S2-2. All dairy farming modules generate milk as main product as well as live animals for slaughter or further fattening (i.e., male calves and culled cows) as co-products. The allocation based on physical causality (so-called "biophysical approach") is applied, following the International Dairy Federation (IDF 2015) guideline, as shown in Table S2-3.

Table S2-1 Herd structure and milk production for dairy farm archetypes (FAO, IDF, IFCN 2014)

IFCN "typical farm"	Breed	(Dairy cows = 100)		Heifers > 1	Heifers < 1	Total	Milk production (kg per year.cow)
		LACTATING COWS	DRY COWS				
AT-14	Brown Swiss	11.8	2.2	5.3	5.4	24.7	6204
BE-45	HF	37.8	7.2	17.0	17.4	79.4	7663
CA-58	HF	48.7	9.3	21.9	22.4	102.3	7273
CH-22	Brown Swiss	18.5	3.5	8.3	8.5	38.8	6305
CZ-80	HF	67.2	12.8	30.3	30.9	141.1	9201
DE-31S	Simmental	26.0	4.9	11.7	12.0	54.7	6576
DE-90N	HF	75.6	14.4	34.0	34.8	158.8	8165
DK-125	HF	105.0	20.0	47.3	48.3	220.5	9352
ES-50NW	HF	42.0	8.0	18.9	19.3	88.2	9328
FI-25	Ayrshire and HF	21.0	4.0	9.5	9.7	44.1	8191
FR-50-W	HF	42.0	8.0	18.9	19.3	88.2	7470
IE-48	HF	82.4	15.6	37.1	37.9	172.9	7000
IT-154	HF	129.4	24.6	58.2	59.5	271.7	8810
NL-70	HF	58.8	11.2	26.5	27.1	123.5	8416
PL-15	HF and local breed	12.6	2.4	5.7	5.8	26.5	6826
SE-60	HF	50.4	9.6	22.7	23.2	105.9	9805
UK-149NW	HF	125.2	23.8	56.3	57.6	262.9	7784
US-2218NY	HF	1895.7	322.3	834.1	853.1	3905.2	10610
US-80WI	HF	67.2	12.8	30.3	30.9	141.1	8963
BR-20S	HF	16.8	3.2	7.6	7.7	35.3	3980
MX-20	HF	16.8	3.2	7.6	7.7	35.3	4810

NZ-351	Cross-bred HF and Jersey	295.0	56.0	132.7	135.7	619.4	4600
PE-7	Brown Swiss	5.3	1.7	2.5	2.5	11.9	2360

Table S2-2 Daily feed intake of lactating cows for dairy farm archetypes (FAO, IDF, IFCN 2014)

IFCN "typical farm"	Pasture alone (no protein)	Pasture with daily ration of protein	Hay, silage, haylage, agricu-ltural residues	Grain / non-processed concen-trate	Compound feed / processed concen-trate	Daily feed intake (KG DMI / DAY.COW)
AT-14	0%	0%	84%	0%	16%	23
BE-45	0%	2%	77%	0%	21%	22
CA-58	0%	17%	44%	21%	18%	18
CH-22	20%	20%	35%	14%	11%	17.5
CZ-80	0%	9%	64%	4%	23%	18
DE-31S	0%	0%	71%	10%	19%	18
DE-90N	0%	2%	70%	5%	23%	18.5
DK-125	0%	0%	68%	13%	19%	18
ES-50NW	6%	20%	29%	0%	45%	22.5
FI-25	0%	0%	56%	32%	12%	15.5
FR-50-W	13%	14%	52%	0%	21%	20.1
IE-48	27%	27%	26%	0%	20%	16
IT-154	0%	0%	70%	9%	21%	23
NL-70	0%	21%	52%	1%	26%	19
PL-15	9%	20%	66%	5%	0%	18
SE-60	0%	4%	58%	0%	38%	20
UK-149NW	10%	23%	41%	4%	22%	22
US-2218NY	0%	0%	49%	4%	47%	25.6
US-80WI	0%	0%	63%	30%	7%	24
BR-20S	0%	65%	17%	1%	17%	16
MX-20	0%	8%	54%	0%	38%	12.5
NZ-351	83%	0%	17%	0%	0%	14.3
PE-7	42%	42%	0%	0%	16%	8.5

Table S2-3 Milk production, BMR and allocation to milk for dairy farm archetypes

IFCN "Typical farm"	Milk production (kg per year.cow)	BMR ratio (M_{meat}/M_{milk})	kg FPCM / kg raw milk	Allocation to milk
AT-14	6204	0.0238	1.0095	85.6%
BE-45	7663	0.0245	0.9857	85.2%
CA-58	7273	0.0258	1.0095	84.4%
CH-22	6305	0.0235	1.0095	85.8%
CZ-80	9201	0.0204	0.9424	87.7%
DE-31S	6576	0.0265	0.9976	84.0%
DE-90N	8165	0.0295	1.0095	82.2%
DK-125	9352	0.0201	1.0170	87.9%

ES-50NW	9328	0.0201	0.9230	87.9%
FI-25	8191	0.0213	1.0289	87.1%
FR-50-W	7470	0.0322	1.0019	80.6%
IE-48	7000	0.0268	1.0095	83.8%
IT-154	8810	0.0198	1.0289	88.0%
NL-70	8416	0.0223	1.0289	86.5%
PL-15	6826	0.0275	0.9706	83.4%
SE-60	9805	0.0191	1.0214	88.4%
UK-149NW	7784	0.0241	0.9781	85.4%
US-2218NY	10610	0.0210	0.9900	87.3%
US-80WI	8963	0.0209	1.0095	87.4%
BR-20S	3980	0.0471	1.0019	71.5%
MX-20	4810	0.0307	1.0019	81.4%
NZ-351	4600	0.0404	1.0753	75.6%
PE-7	2360	0.0657	0.9900	60.3%

Manure management systems

In parallel, emission modules for different **manure management systems (MMS)** were created based on IPCC (2006) emission factors for CH4, N2O and NH3. Beside manure produced on pasture, it is considered that all other manure is collected at the barn or the feedlot. Six manure management systems are represented with up to three climate conditions (cool, temperate, warm) as shown in Table S2-4 below. For Canada, the data is from DFC (2012)

Table S2-4 Shares of manure management systems for dairy cattle in different regions (FAO 2010, except Canada: DFC 2012)

Region	Manure storage					
	LAGOON	LIQUID/SLURRY	SOLID STORAGE	DRYLOT	PASTURE/ RANGE	DAILY SPREAD
Western Europe (1)	0%	38%	36%	0%	22%	4%
Eastern Europe (2)	0%	22%	61%	0%	14%	3%
United States	12%	32%	31%	0%	16%	9%
Canada	3%	50%	34%	0%	13%	0%

(1) The following countries are considered part of Western Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom

(2) The following countries are considered part of Eastern Europe: Czech Republic, Greece, Hungary, Poland, Romania, Slovakia

National mix of archetypes

Archetypes of typical dairy farms and MMS are combined in different proportions as to represent the typical mix of dairy systems in different countries. These mixes are mainly based on qualitative information retrieved from IDF and IFCN (FAO, IDF, IFCN 2014) and Eurostat 2013 data.

Methane emissions from enteric fermentation

Methane emissions from enteric fermentation are calculated based on the IPCC (2006), Tier 2, formula below. This approach is supported by the International Dairy Federation (IDF 2015).

Methane from Enteric fermentation: $EF = \left[\frac{GE*\left(\frac{Ym}{100}\right)*365}{55,65}\right]$

EF = CH_4 emission [kg CH_4/head/year]

GE = gross energy intake [MJ/head/day]

Ym = methane conversion factor [GE converted to CH_4]

With Ym for cattle (except feedlot fed) = 6.50

Ym for cattle (feedlot fed) = 3.0

55.65 MJ/kg CH4 = energy content of methane

GE intake is estimated from DM intake, by using the default value of 18.45 MJ/kg DM from IPCC (2006).

Table S2-5 National mixes (%) for milk production based on dairy farm archetypes

IFCN typical farm	AT	BE	CA	CH	CZ	DE	DK	ES	FI	FR	GR	HU	IE	NL	PL	PT	RO	SE	SK	UK	US
AT-14	50%			30%	10%	20%		10%		25%					30%		10%	5%		10%	
BE-45		40%						10%		25%				13%						10%	
CA-58			40%																		
CH-22				50%		15%				10%											
CZ-80					50%							10%					3%		10%		
DE-31S	40%	30%		10%	10%	20%					50%							16%			
DE-90N						25%															
DK-125						10%	88%		10%	5%				10%				50%			
ES-50NW								50%								50%					
FI-25									50%					6%						5%	
FR-50-W	10%			10%		10%				35%		10%	25%							5%	
IE-48													24%								
IT-154											10%										
NL-70							12%	10%	15%					47%						20%	
PL-15									25%			50%		5%	25%		12%			15%	
SE-60																		29%			
UK-149NW		30%	15%		30%							30%		19%		25%			70%	35%	35%
US-2218NY																					25%
US-80WI			45%																		40%
BR-20S								10%								25%					
MX-20								10%			40%										
NZ-351													31%	20%							
PE-7													20%		45%		75%		20%		
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100 %*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100 %*	*100%*	*100%*	*100 %*

S3.3 Allocation procedures

A common methodological decision in LCA occurs when the system being studied produces co-products, such as vegetable oil and meal from oil extraction, or milk and meat from dairy farming. When systems are linked in this manner, the boundaries of the system of interest must be widened to include the system using all co-products, or the environmental impacts of producing the linked product must be attributed to the different co-products in the systems. The allocation method used for background processes depends on the approach applied in the ecoinvent database.

Allocation for crop ingredients and vegetable oils

Based on the Methodological Guidelines for Agricultural Products (Nemecek et al. 2015), economic allocation was used by default for crop co-products at the farm. Prices were calculated as average values between 2009-2012, when available. This approach is also supported by the FAO LEAP Guidelines (LEAP 2015). Economic allocation was also applied in the multi-output processes of oil extraction, hence ensuring consistent allocation of upstream processes among the different systems under investigation (i.e., vegetable oils for PB spreads and feed for dairy cattle) (FEFAC 2016; LEAP 2015; Nemecek et al. 2015).

Table S4-1 Crop or seed to oil ratio and allocation factors for various vegetable oils

Crude oil	Fruit/seed to oil ratio	Allocation to crude oil (%)	Allocation to other co-products (%)
Coconut oil	6.9	91.3%	8.7%
Linseed oil	3.3	70%	30%
Maize oil	18.3	18%	82%
Olive oil	4.9	46.1%(1); 30.3%(2); 20.3%(3)	3.3%
Palm kernel oil	2.1(4)	89.8%	10.2%
Palm oil	5.0	86.3%	13.7%
Rapeseed oil	2.5	76.3%	23.7%
Shea butter	2.6	100%	0%
Soybean oil	5.2	38.3%	61.7%
Sunflower oil	3.5	79.8%	20.2%

(1) Extra virgin olive oil; (2) Virgin olive oil ; (3) Lampante olive oil
(4) Palm kernel oil is obtained from palm kernels which are co-products from crude palm oil production.

Allocation for dairy products

Upstream burdens and activities were allocated to the raw Fat and Protein Corrected Milk (FPCM), using the IDF formula (IDF 2015) and live animals based on biophysical criteria following the ISO hierarchy of allocation procedure (ISO 14044). This approach is supported by the European PEF category rules for Dairy products (EDA 2016). In our study, the allocation to milk ranges from 63% in Romania to 88% in Denmark due to spatial variability of the ratio between yield of meat and yield of milk across different countries. This is consistent with a previous study by (Thoma et al. 2013), which reports majority of studies allocate 75–90% of environmental burdens to milk compared to the beef co-product. In addition, various studies show the difference of allocating burdens between milk and meat are less than 20% when comparing different allocation methods (Cederberg and Stadig 2003; Gerber P, et al. 2010; O'Brien et al. 2014). Manure was considered as a residue, with no economic value; emissions from manure storage were allocated to the co-products from the dairy farm (raw milk and live animals for slaughter or further fattening). Dead animals were considered as waste.

Butter and cream are made by removing fat from raw milk. Butter production leads to skimmed milk and buttermilk as co-products, while cream production also generates skimmed milk. The allocation of the upstream burden embodied in the input raw milk as well as other inputs (energy, water, refrigerants) and outputs (wastewater, etc.) is based on the dry weight (i.e., dry matter content) of butter and cream and its co-products, following the IDF (2015) and the European PEF category rules for Dairy products EDA (2016). For the allocation factor based on dry matter content, the allocation factor (AF) is calculated for each product (i) using the following equation:

$$AF_i = \frac{DM_i \times Q_i}{\sum_{i=1}^{n} (DM_i \times Q_i)}$$

Where:

- AF_i: allocation factor for product i;
- DM_i: dry matter content of product i (expressed as dry matter or as weight by mass of dry matter/weight by mass of product i)
- Q_i: quantity of product i output to the production site or from the unit operation (kg of product i).

Table S4-2 Butter processing inventory data

Inputs	Amount	Unit
Raw milk (national mix)	19.8	kg
Cream (national mix)	2.1	kg
Yeast	33	mg
Tap water	1.5	kg
Nitric acid	31	g
Sodium hydroxide	17	g
Natural gas	0.1	MJ
Electricity (national mix)	1.5	kWh
Dairy facility (capital goods)	6.21E-05	m3
OUTPUTS	**AMOUNT**	**UNIT**
Butter	1	kg
Skimmed milk	17.7	kg
Buttermilk	1.1	kg
Wastewater	0.00132	m3

Table S4-3 Butter processing co-products allocation

Co-products	Dry matter	Amount	Allocation
Butter	84.4%	1 kg	33.2%
Skimmed milk	9.1%	17.7 kg	63.3%
Buttermilk	8.0%	1.1 kg	3.5%

Allocation for transportation related activities

All transport was assumed to be weight-limited due to the high density of most ingredients (oils and raw milk) and final products. The ecoinvent database provides road, rail and sea transportation inventory based on a weight-limited approach. A default utilization ratio of 64% was used, which includes empty return trips.

Allocation for packaging production and end-of-life activities

For all packaging recycling processes, in alignment with ecoinvent methodology, the "cut-off by classification" approach was used to allocate recycled content and recycling at end-of-life(Ekvall and Tillman 1997). The underlying philosophy of this approach is that primary (first) production of materials is allocated to the primary user of a material. If a material is recycled, the primary producer does not receive any credit for the provision of any recyclable materials. Consequently, recyclable materials are available burden-free to recycling processes, and

secondary (recycled) materials bear only the impacts of the recycling processes. Given the nature of the products under investigation, this has a negligible influence on overall results as only the packaging materials are affected by this assumption.

S3.4 Sensitivity analysis

- **Sensitivity analysis: influence of functional unit choice**

PB spreads, butter and dairy spreads are assumed to be directly substitutable in equivalent quantity of mass. Some PB spreads, however, have slightly higher densities than butter due to water being denser than fat. It could, therefore, be argued that spreadable products are substitutable in equivalent quantity of volume. A sensitivity analysis is conducted that the PB spread with the highest density was used to test this hypothesis. Similarly, the assumption was made that PB creams and dairy creams are directly substitutable in equivalent quantity of mass, considering they have similar densities. Some PB creams have a lower fat content than dairy cream; however, comparative tests and expert judgement showed that it does not affect the amount used for whipping or cooking. Since the nutritional profile of the PB spreads and dairy products are different, an alternative FU, based on total fat content, was also assessed in a sensitivity analysis. Total fat content was selected, rather than protein or energy content, as fat may be a relevant consideration for the consumer when using the product for spreading or baking and the main nutritional function is the addition of fat to the diet, although fat for creams is usually for taste/performance and not for nutrition purposes. Further sensitivity analyses based on specific aspects related to nutrient content have not been assessed. In general, a dietary pattern that is higher in plant-based foods, such as vegetables, fruits, whole grains, legumes, nuts, seeds, and liquid vegetable oils and lower in calories and animal-based foods is considered to be healthier than the current average western diet according to 2015 Dietary Guidelines Advisory Committee (McGuire S et al. 2016) and the EAT–Lancet Commission on healthy diets from sustainable food systems (Willett et al. 2019). Several countries explicitly align health and environmental sustainability into their dietary recommendations (Gonzales Fischer and Garnett 2016).

- **Alternative functional unit based on volume**

This sensitivity analysis evaluated whether the FU based on volume rather than mass might alter the conclusions, since low-fat PB spreads have a higher density than higher-fat products, and density is a function of mass and volume (kg/L). From the PB spreads studied, the highest density was 0.991 kg/L and the lowest was 0.929 kg/L, whereas butter typically has a density

of 0.911 kg/L. The sensitivity analysis considered a “worst case” approach where all PB spreads assessed had the highest density (0.991 kg/L) and showed that changing the FU affected the different reference flows. In the most extreme case, the amount (kg) of low fat PB spread that was needed to fulfil the same volume-based function as butter was 9% higher compared to the baseline assessment. By doing so, the relative impacts of PB spreads increased in the same proportions. This analysis was not performed for PB creams. Although some PB creams do have a lower fat content than cream, it does not affect the amount used for whipping or cooking (proprietary knowledge). The general trend for the LCA results were similar when considering a FU based on mass or volume.

- **Functional unit based on total fat content**

The influence of considering a FU based on the total fat content, rather than on the total fresh mass, was investigated because most PB spreads have a lower fat content than butter. Such consideration seems of low relevance when products are used for spreading based on volume, but could be pertinent when used in baking if, for instance, the % of fat used in a cake recipe influences the quality of the cake in terms of taste/performance. With a variability ranging from 300 - 800 g/kg, the total fat in a PB spread can also be a differentiating factor for the consumer. PB creams often have a lower fat content than dairy cream, some even with a particularly low-fat content of < 100 g/kg. Butter typically has a total fat content of 800 g/kg and dairy creams in the present study had a total fat content ranging from 150 to 400 g/kg. For most scenarios and impact categories, the original conclusion holds when changing the FU. This is particularly true for climate change, land occupation and water scarcity. As expected, low-fat spreads were more sensitive than higher-fat spreads. For a few very low-fat PB cream products (< 100 g/kg), however, the consideration of the fat-based FU alters the conclusion and results are favorable for cream. This shows that the choice of a fat content-based FU is influential, and may alter some of the original conclusions, particularly when a PB product has a very low-fat content compared to butter or cream products. Sensitivity results for fat content based functional unit are available in Fig. S7-1 for all 21 countries, Fig. S7-2 for 3 Nordic countries including dairy spreads, and Fig. S7-3 for plant-based cream and dairy creams

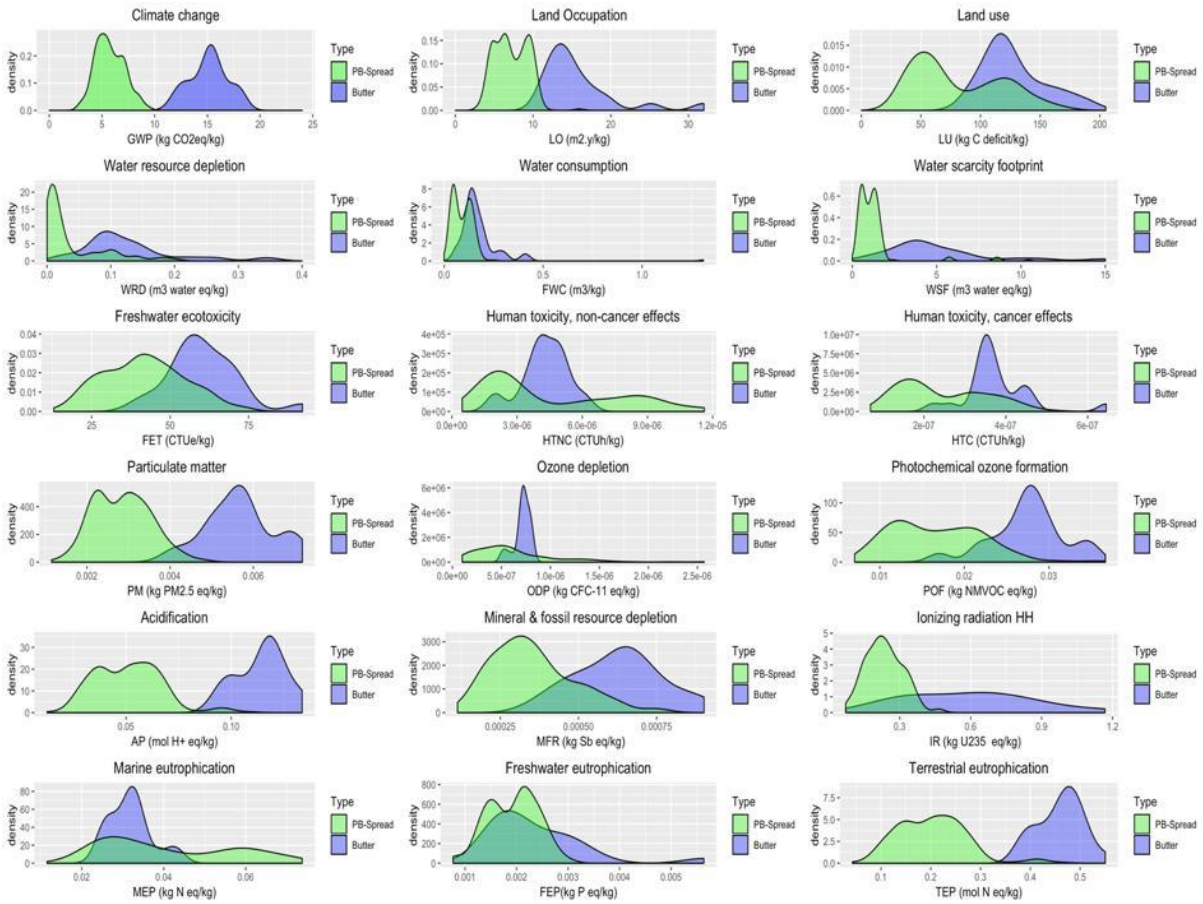

Fig. S7-1 Comparing environmental impacts between PB spread and butter products in all 21 markets based on fat content functional unit

A few extreme values are removed from the plotting (including the data points with water resource depletion > 0.4 m_3 water-$_{eq}$/kg; Water consumption > 1.31 m_3/kg and Water scarcity footprint>15 m_3 water-$_{eq}$/kg)

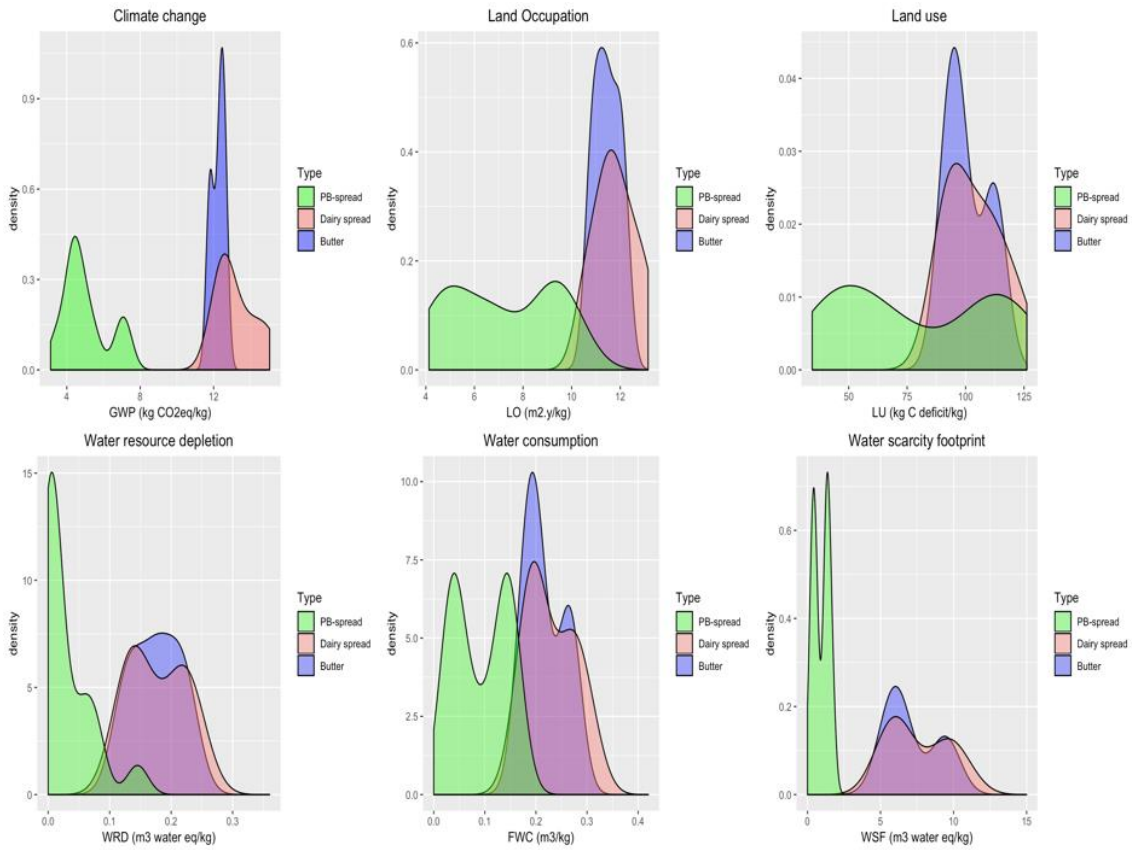

Fig. S7-2 Comparing environmental impacts between PB spread and butter products in 3 Nordic markets based on fat content functional unit

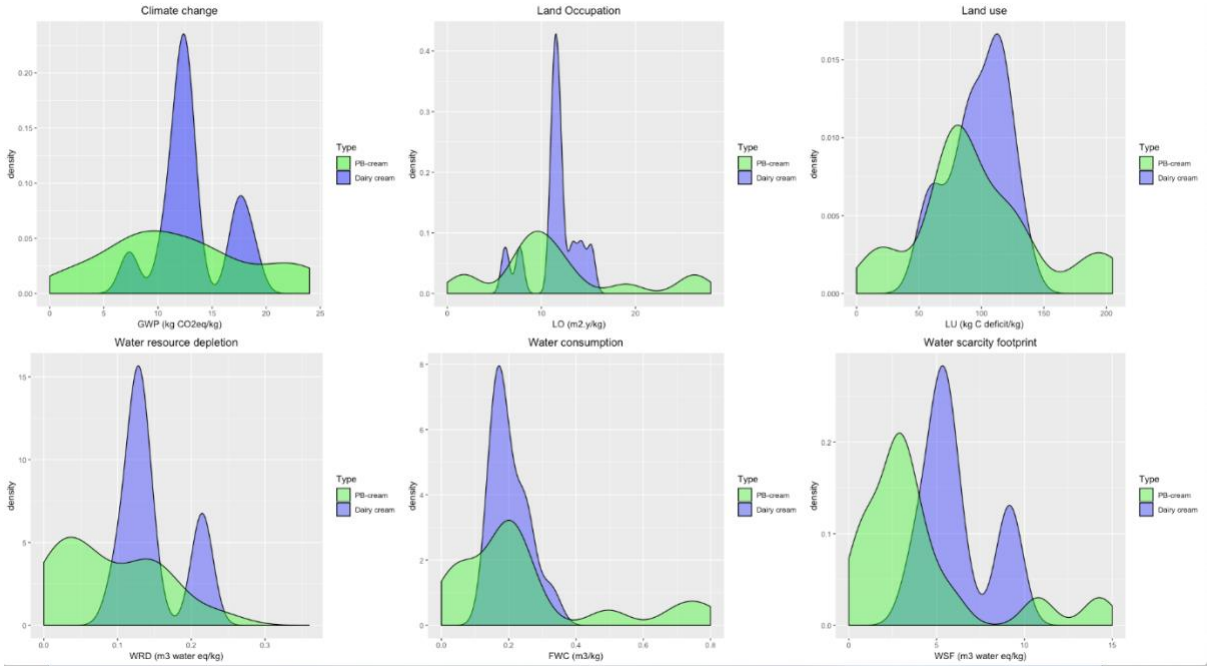

Fig. S7-3 Comparison of environmental impacts between PB cream and dairy cream products in all 21 markets based on fat content functional unit

- **Sensitivity analysis: influence of allocation method for vegetable oil extraction**

A sensitivity analysis was performed considering mass allocation in the vegetable oil extraction processes rather than the default economic allocation. In the baseline assessment, economic allocation was applied as per the Product Environmental Footprint Category Rules (PEFCR) for olive oil (Schau et al. 2016). Mass allocation was applied in the main vegetable crude oil extraction processes (sunflower, palm, palm kernel, rapeseed, coconut, linseed, maize, olive) considering allocation factors from v3.0 Blonk Agri-footprint (2015). Mass allocation generally attributes a lower share of the upstream burden to crude oil compared to economic allocation. The only exception is maize oil with a mass allocation factor of 19.6% and an economic allocation factor of 18.0% for the crude oil. As illustrated in **Fig. S7-4** for climate change impacts, the analysis showed that the total impacts of PB spreads and PB creams when mass allocation was applied was systematically lower than calculated for the baseline scenario, showing that the application of economic allocation for oil extraction and processing is rather conservative and is not likely to change the conclusions of the study.

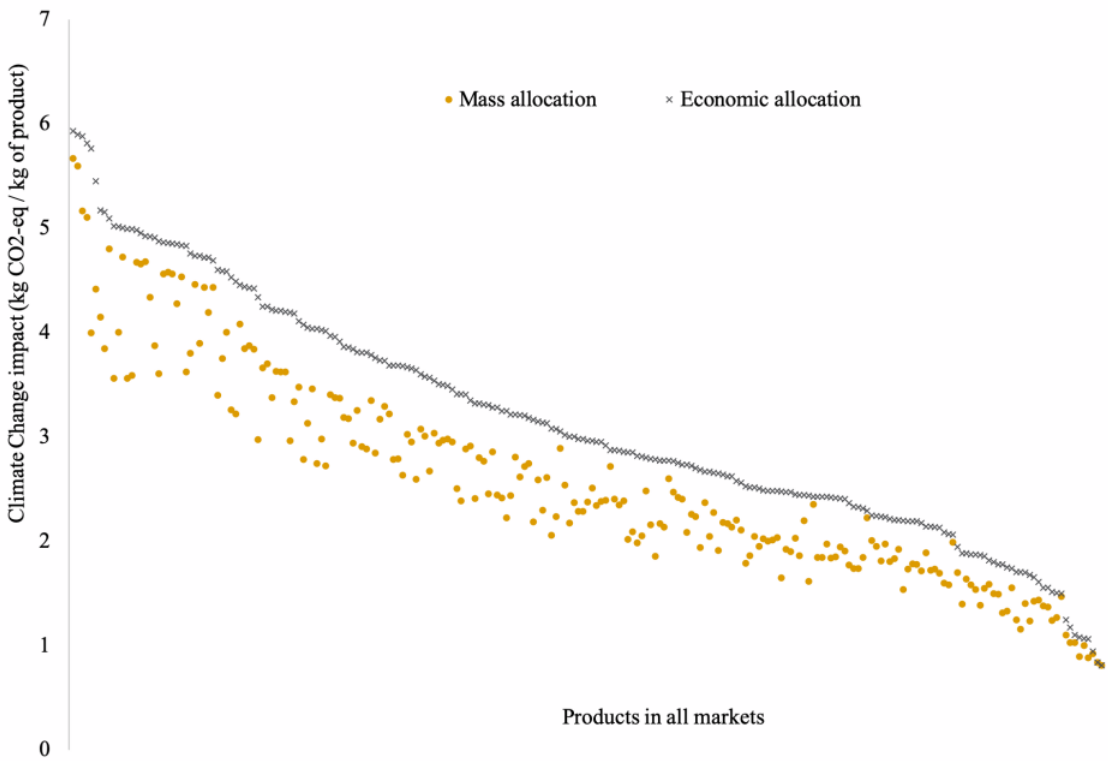

Fig. S7-4 Impact of allocation on climate impact results of all plant-based products in every market (Each point represents a different PB spread or PB cream scenario)

- **Sensitivity analysis: influence of packaging choice**

Packaging production accounts for 3% to 10% of life cycle climate change impacts for all PB spreads in the baseline scenarios. The variability of climate change impacts of various packaging types for PB spreads was relatively small (0.15-0.28 kg CO_2-eq/kg of spread). For a single packaging type, the smaller the package volume the higher the impact per kg of spread, therefore in the baseline assessment, tubs with the smallest volumes (225 g and 250 g) were considered for most scenarios. For PB cream products, climate change impacts of PET bottle packaging (baseline) production (0.31 kg CO_2 eq/kg of PB cream) is 16 times higher than the alternative multi-layer liquid board packaging, e.g. Tetra Pak (0.02 kg CO_2-eq/kg of PB cream). Therefore, in this study, the sensitivity of switching from PET bottle to liquid board packaging for PB cream was performed for German PB creams (**Fig. S7-5**). Switching from a PET bottle to liquid board packaging could lead to a decrease in life cycle climate change impacts of PB cream products (14% to 26%), but the recycling infrastructure for these types of packaging might not be readily developed, depending on the market, compared to PET recycling systems. Overall, the relative differences between PB creams and dairy creams remain similar therefore, the choice of packaging in the LCA model is not sensitive and thus not likely to change results.

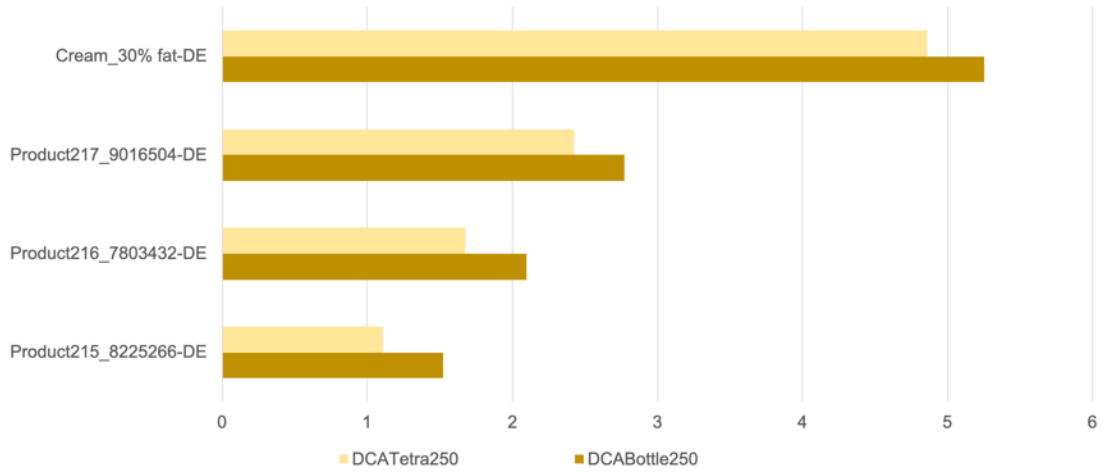

Fig. S7-5 Impact on climate change (kg CO2 eq/kg) depending on packaging type for PB cream products

- **Sensitivity analysis: certified renewable electricity for PB spread production**

Certified electricity from renewable sources is purchased in most factories producing the PB spreads in this study. When electricity from certified (renewable) origins was known, this was considered in the baseline model. A sensitivity analysis was performed to evaluate whether the use of the national electricity consumption mix affects the LCA results. The analysis focused on climate change impacts, which is generally the main driver for purchasing certified electricity from renewable sources. The assessment shows that for one PB cream from Germany the benefit of using certified electricity could reduce life cycle climate change impacts by 8%. Overall, this parameter did not change results with respect to the comparative assessment of PB spreads vs. butter, or PB creams vs. dairy cream.

S3.5 Tables

Table S1 Number of PB spreads compared to butter and dairy spread in the different countries

Country	PB spreads	Butters	Dairy spreads
Austria	13	1	0
Belgium	9	1	0
Canada	7	1	0
Czech Republic	13	1	0
Denmark	4	1	1
Finland	15	1	3
France	7	1	0
Germany	17	1	0
Greece	7	1	0
Hungary	11	1	0
Ireland	10	1	0
Netherlands	11	1	0
Poland	8	1	0
Portugal	6	1	0
Romania	8	1	0
Slovakia	11	1	0
Spain	11	1	0
Sweden	15	1	3
Switzerland	9	1	0
United Kingdom	11	1	0
United States	9	1	0
Total	**212**	**21**	**7**

Table S2 Number of PB creams compared to dairy creams in the different countries

Country	PB creams	Dairy creams
Austria	1	1
Finland	6	5
Germany	3	1
Sweden	5	4
Switzerland	1	1
Total	**16**	**12**

Table S3: Indicators and related assessment models used and minimal significance level

Impact category or LCI indicator	Model	Unit	Source[3]	Class[1]	Minimal significance level[2]
Climate change	Bern model – Global Warming potentials (GWP) over a 100-year time horizon	kg CO_2 eq	IPCC, 2007	I	Factor 2
Ozone depletion	EDIP model based on the ODPs of the WMO w/ infinite time horizon	kg CFC-11 eq	WMO, 1999	I	Factor 2
Human toxicity – non-cancer effects	USEtox® model	CTUh	Rosenbaum et al., 2008	II/III	Factor 10
Human toxicity – cancer effects	USEtox® model	CTUh	Rosenbaum et al., 2008	II/III	Factor 5
Particulate matter	Humbert, 2009	kg $PM_{2.5}$ eq	Humbert, 2009	I	-20%
Ionising radiation	Human Health effect model	kg U^{235} eq	Dreicer et al., 1995	II	Factor 2
Photochemical ozone formation	LOTOS-EUROS model	kg NMVOC eq	van Zelm et al., 2008	II	Factor 2
Acidification	Accumulated Exceedance model	mol H+ eq	Seppälä et al.,2006; Posch et al., 2008	II	Factor 2
Terrestrial eutrophication	Accumulated Exceedance model	mol N eq	Seppälä et al.,2006; Posch et al., 2008	II	-33%
Freshwater eutrophication	EUTREND model	kg P eq	Struijs et al., 2009	II	Factor 2
Marine eutrophication	EUTREND model	kg N eq	Struijs et al., 2009	II	-33%
Freshwater ecotoxicity	USEtox® model	CTUe	Rosenbaum et al., 2008	II/III	Factor 5
Mineral & fossil resource depletion	CML 2002 model	kg Sb eq	van Oers et al., 2002	II	Factor 5
Land use	Soil Organic matter (SOM) model	kg C deficit	Milà i Canals et al., 2007	III	-33%
Water resource depletion	Swiss Ecoscarcity model	m^3 water eq	Frischknecht et al., 2008	III	Factor 4
Land occupation	LCI indicator	m^2.y	n/a	n/a	-33%
Water scarcity footprint	AWARE 100 model	m^3 water eq	Boulay et al. 2017	n/a	Factor 2
Water consumption	LCI indicator	m^3	n/a	n/a	-33%

[1] The European Commission Joint Research Centre (JRC) classifies every impact category according to the maturity and reliability of its underlying model:

- Level I: recommended and satisfactory
- Level II: recommended, but in need of some improvements
- Level III: recommended, but to be applied with caution. Models classified at Level III are likely to evolve in a near future.

[2] Assuming inventory flows in foreground processes and in background databases are properly and consistently modelled, a minimal significance level can be estimated when comparing PB fat spreads and dairy scenarios. The minimal significance level characterizes the smallest difference among two compared products, and for each environmental indicator, which can be considered significant (e.g., a "Factor 2" involves that if one product has an impact of 100, the compared product shall have an impact smaller that 50, or higher than 200, in order for the difference to be significant). The significance levels are specific to the system under investigation in the sense that they attempt to consider the uncertainty on the inventory flows (e.g., farm inputs or direct emissions from fertilizer application), the degree of correlation between inventory flows in the systems compared, and the uncertainty on the characterization factors used to calculate each and single impact indicator result. Given the absence of absolute references for this exercise, this estimation is based on Quantis' expert judgement considering its experience in developing the World Food LCA Database and some part of the ecoinvent database, and in following closely the development of the ILCD 2011 Midpoint+ method through many years in the context of the European PEF initiative.

[3] Detailed references for each indicator are available from JRC-IES (2011).

Table S4: Main data sources for the bill of activities of different life cycle stages

System	Process stage	Data source(s)
PB spreads and PB creams	Ingredient's supply: ingredient type, quantity and sourcing origin; oil extraction, refining and further processing; Production of other ingredients; Transport to spreads production factory	Upfield (2015) (primary data, for types and amounts)
		FAOSTAT (2006-2011) (for sourcing of ingredients)
		Blonk Agri-footprint (2015) (for oil extraction and processing)
		Schau et al (2016) (for olive oil extraction and refining)
		WFLDB, Agri-footprint, Quantis (2016) (for crop production)
	Production: energy, water, consumables, waste, emissions	Upfield (2015) (primary data, for types and amounts)
		Ecoinvent 3.3 (for upstream production)
	Packaging: type and amount	Upfield (2015) (primary data, for types and amounts)
		Ecoinvent 3.3 (for upstream production)
	Distribution: transport and storage	Upfield (2015) (primary data),
		Humbert and Guignard (2015) (for storage energy use)
		Ecoinvent 3.3 (for upstream processes)
	Use stage: refrigeration at consumer home	De Schryver et al. (2016)
		Ecoinvent 3.3 (for electricity)
	Packaging end-of-life: transport and treatment	EDA (2016), Eurostat (2014), US EPA (2015)
		Ecoinvent 3.3 (for treatment activities)
Dairy products	Raw milk production and transport to processing factory	EDA (2016), FAO-IDF-IFCN (2014), FAO (2010)
	Butter and cream processing: energy, water, consumables	EDA (2016)
		Ecoinvent 3.3 (for upstream production)
	Packaging: type and amount	EDA (2016)
		Ecoinvent 3.3 (for upstream production)
	Distribution: transport and storage	EDA (2016), Humbert and Guignard (2015) (for storage energy use)
		Ecoinvent 3.3 (for upstream processes)
	Use stage: refrigeration at consumer home	EDA (2016), De Schryver et al. (2016)
		Ecoinvent 3.3 (for electricity)
	Packaging end-of-life: transport and treatment	EDA (2016), Eurostat (2014), National Statistics (US and CA)
		Ecoinvent 3.3 (for treatment activities)

Table S5 Carbon pools accounting in land transformation

Carbon pool	Land transformation to annual or perennial crop				
	From primary forest	From secondary forest	From perennial crop	From annual crop	From grassland
AGB [(1)]	8% harvested and stored 92% emitted (20% burned, 72% by decay)			100% emitted by decay Net carbon capture may occur in certain cases and is considered	
BGB [(2)]	100% emitted by decay				
DOM [(3)]	100% emitted by decay			Ignored	
SOC [(4)]	SOC change according to IPCC 2006, including peat drainage emissions. Net carbon capture may occur in certain cases and is considered				

[(1)] Aboveground biomass; [(2)] Belowground biomass; [(3)] Dead organic matter; [(4)] Soil organic carbon

Table S5 provides additional data for the section “2.4.4. Modeling GHG emissions from land use change” of the article

Table S6 Pedigree matrix used for data quality assessment

Indicator score	1	2	3	4	5
Reliability	Verified data based on measurements	Verified data partly based on assumptions or non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate
Completeness	Representative data from all sites relevant to the market considered, over an adequate period to even out normal fluctuations	Representative data from >50 of the sites relevant for the market considered, over an adequate period to even out normal fluctuations	Representative data from only some sites (<<50) relevant for the market considered or >50 of sites but from shorter periods	Representative data from only one sites relevant for the market considered or some sites but from shorter periods	Representativeness unknown or incomplete data from a smaller number of sites and from shorter periods
Temporal correlation	Less than 3 years of difference to the time-period of the dataset	Less than 6 years difference to the time-period of the dataset	Less than 10 years difference to the time-period of the dataset	Less than 15 years difference to the time-period of the dataset	Age of data unknown or more than 15 years of difference to the time-period of the dataset
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown or distinctly different area
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials	Data on related processes on laboratory scale or from different technology

S3.6 Figures

Fig. S1 illustrates the relationship of climate, water and land impact for 211 plant-based spreads with different fat contents sold in various countries. It shows the water and land related impacts have strong positive correlations with the climate change impact. A few exceptions exist for water scarcity footprint weighted by rationalized water scarcity index. This happens to product recipes including the almond nuts ingredient, which are sourced from regions with high water scarcity risk requiring high irrigation water. Overall, there is little risk of shiftting climate change impact to land and water related impact, however, special attention should be paid to agricultral ingredients with high embodied water scarcity footprint.

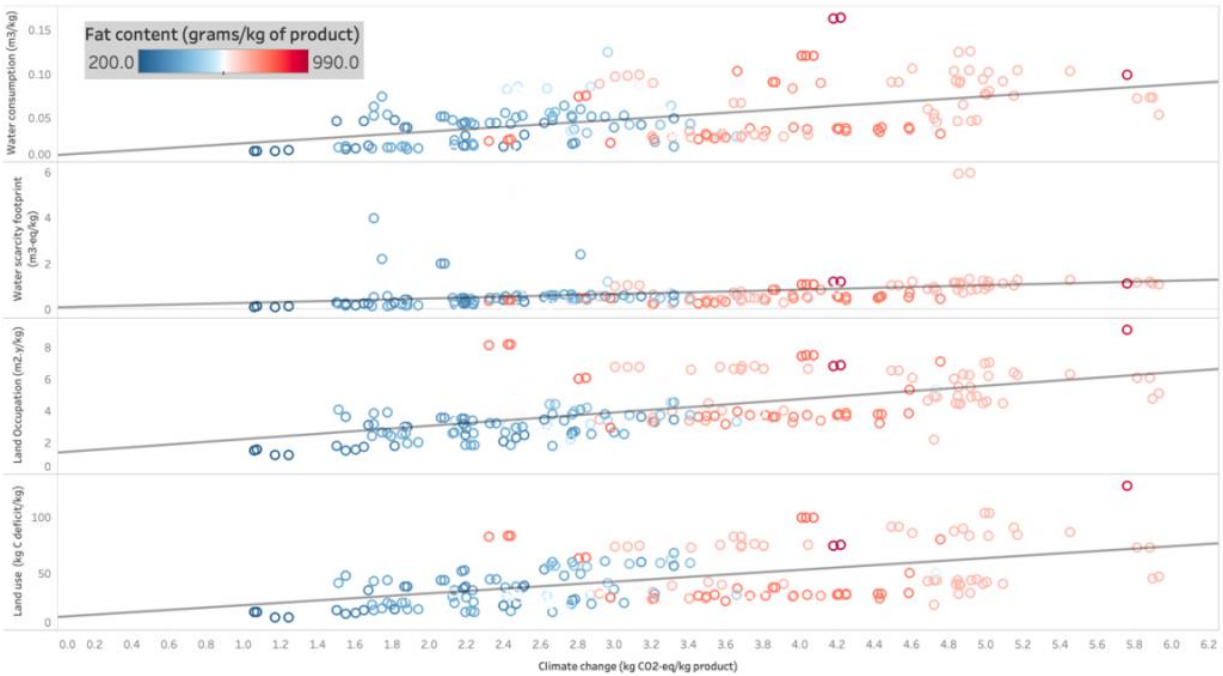

Fig. S1 The relationship of climate, water and land impact for 211* plant-based spreads with different fat contents (*one extreme value is removed)

Fig. S2 below shows the boxplot distribution of climate, water and land impact results by product categories.

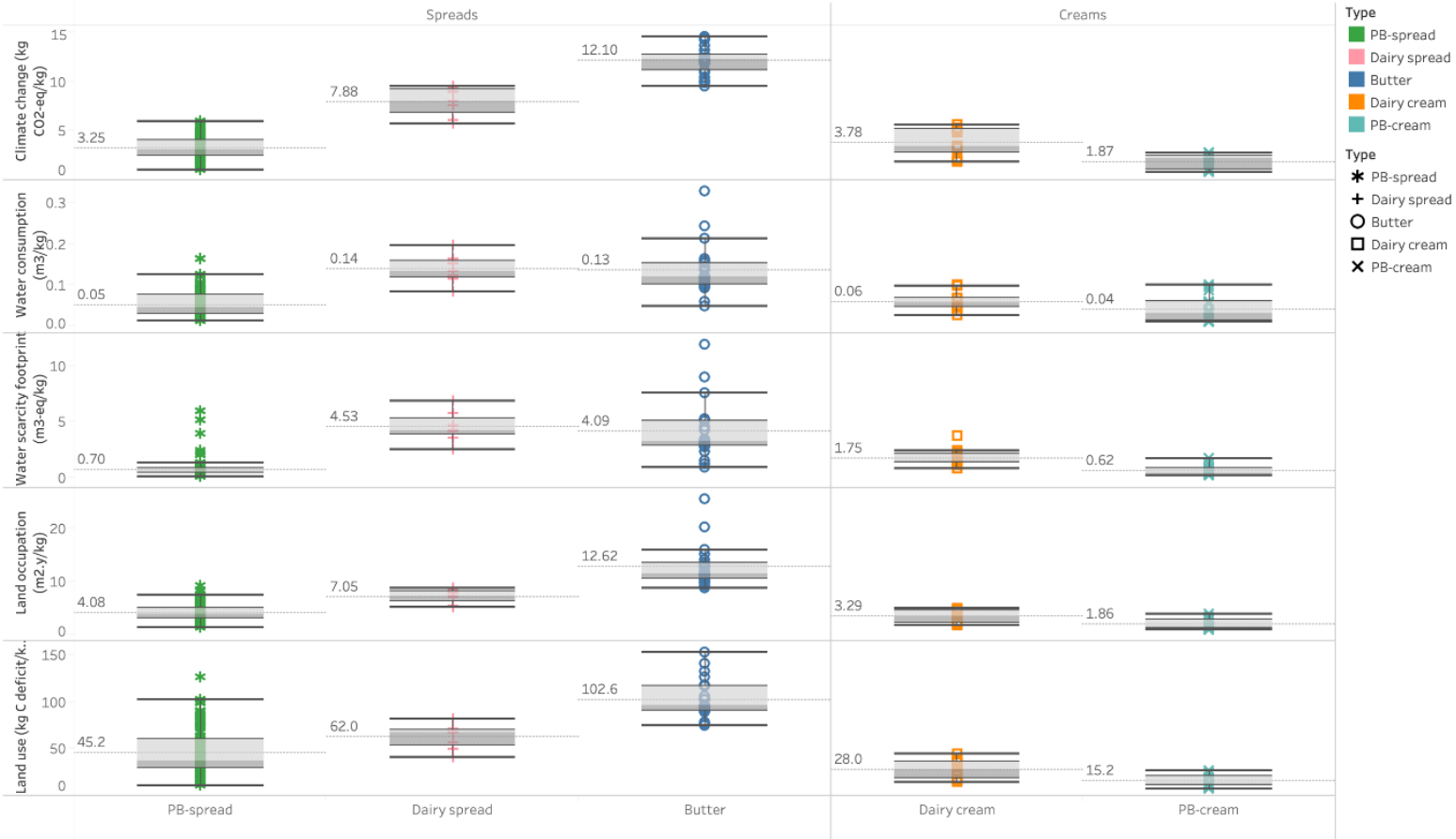

Fig. S2 Impact on climate, water and land of all products (*one extreme PB spread value in Canada is removed. It has higher land occupation and water scarcity footprint impact than dairy butter)

Fig. S3 below shows the results by country and by product categories.

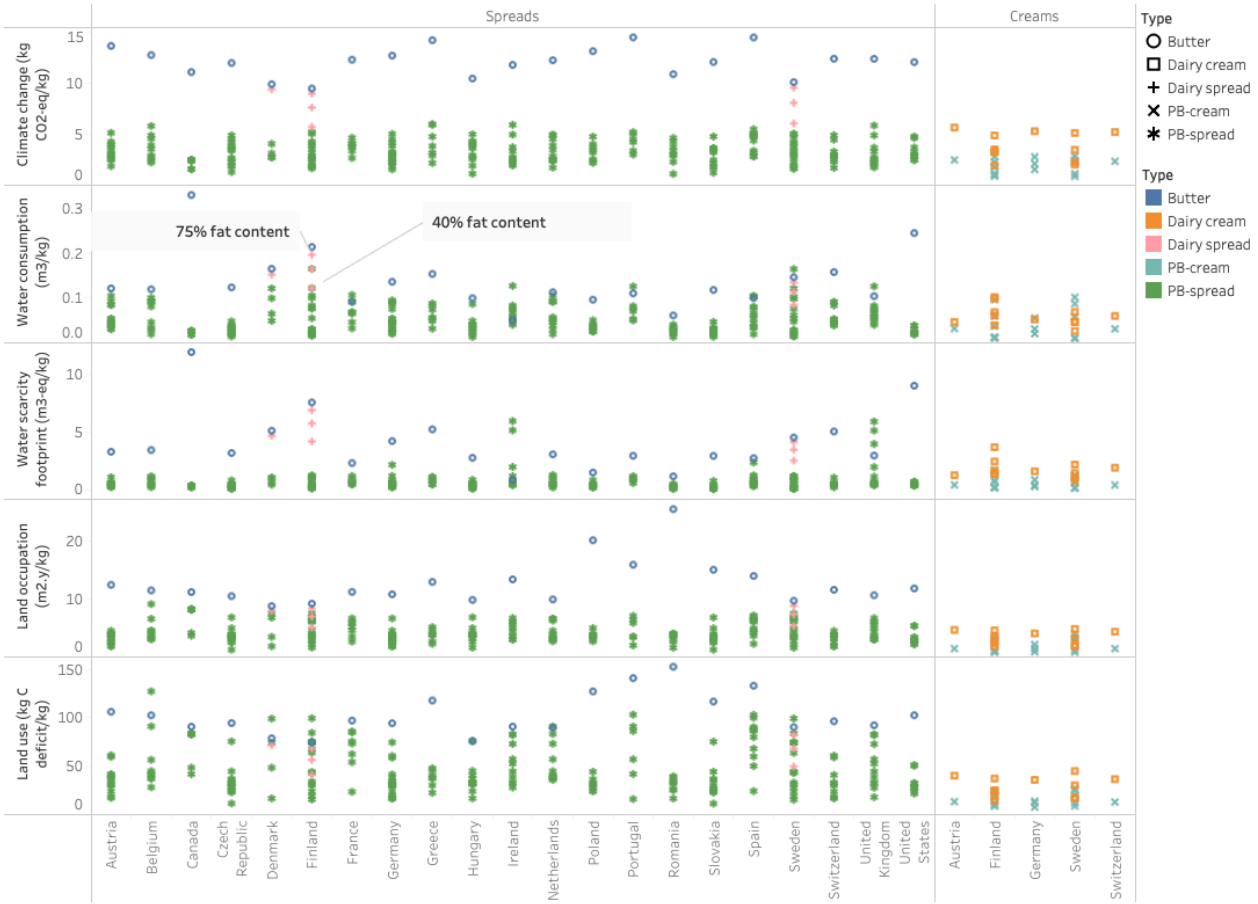

Fig. S3 Impact on climate, water and land of all products by countrie (*one extreme PB spread value in Canada is removed. It has higher land occupation and water scarcity footprint impact than dairy butter)

Additional information for all 18 impact indicators is given in Fig. S4-S6 below for PB products and dairy alternatives. One extreme value is removed from the plotting.

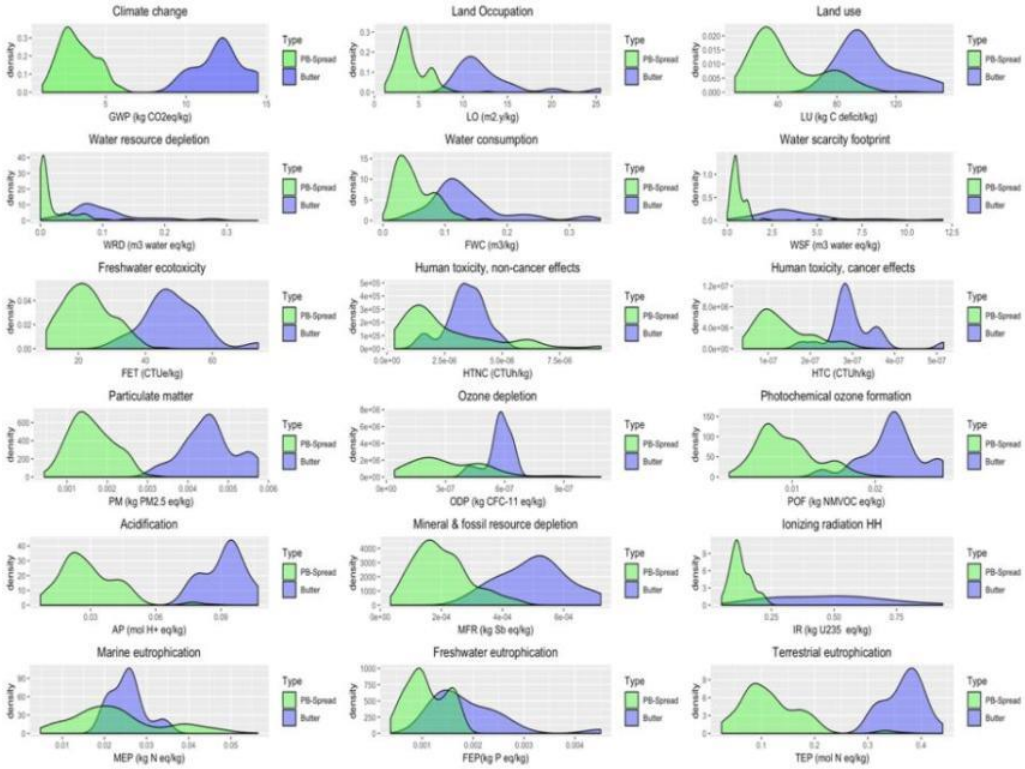

Fig. S4 Comparing environmental impacts between 211 PB-spread and 21 butter products in all 21 markets (the figure is made by using "ggplot 2" package in R software (Wickham et al. 2018). In statistics, kernel density estimation is a useful technique to visualize the shape based on finite data samples as in our study. The *x*-axis shows the respective indicator results. The smaller the range of impact values of different products in x-axis, the higher the density value is. The integral of the shape for each type for a given impact indicator equals to 1, the 100% of probability. The detailed discussions are given below for key environmental impact indicators of interests)

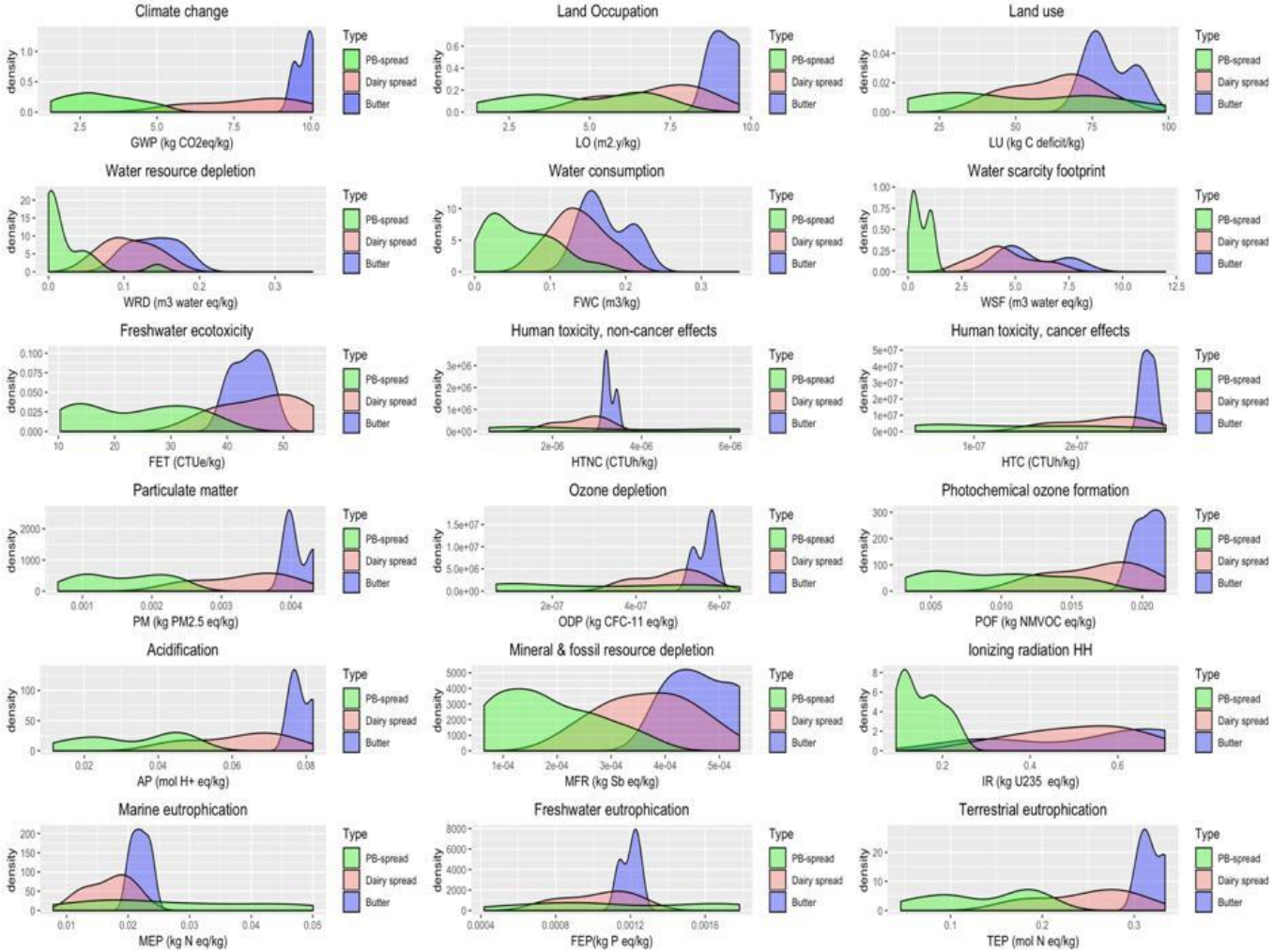

Fig. S5 Comparing environmental impacts between PB-spread and butter products in 3 Nordic markets (Denmark, Norway and Sweden)

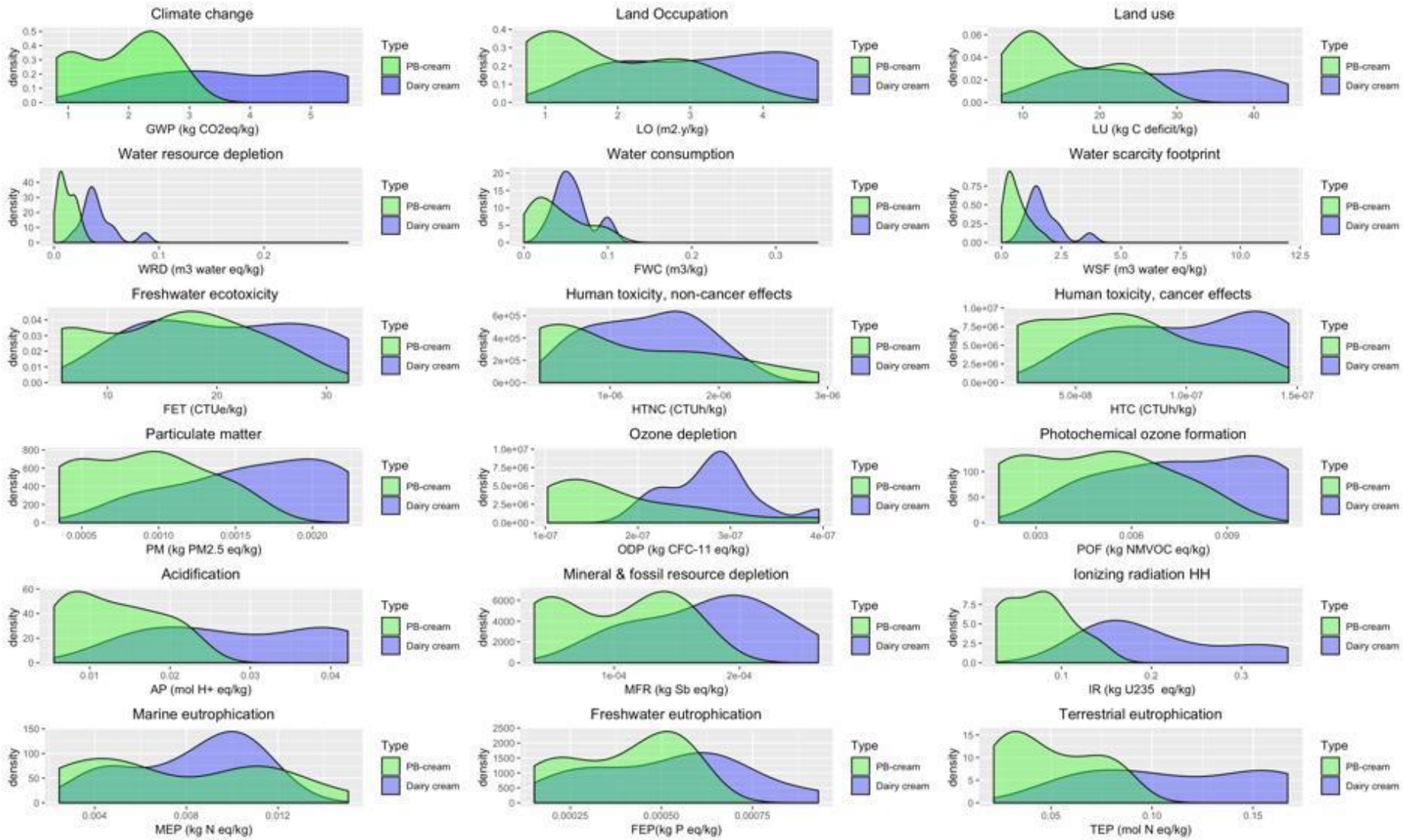

Fig. S6 Comparison of environmental impacts between PB cream and dairy cream products in all 21 markets

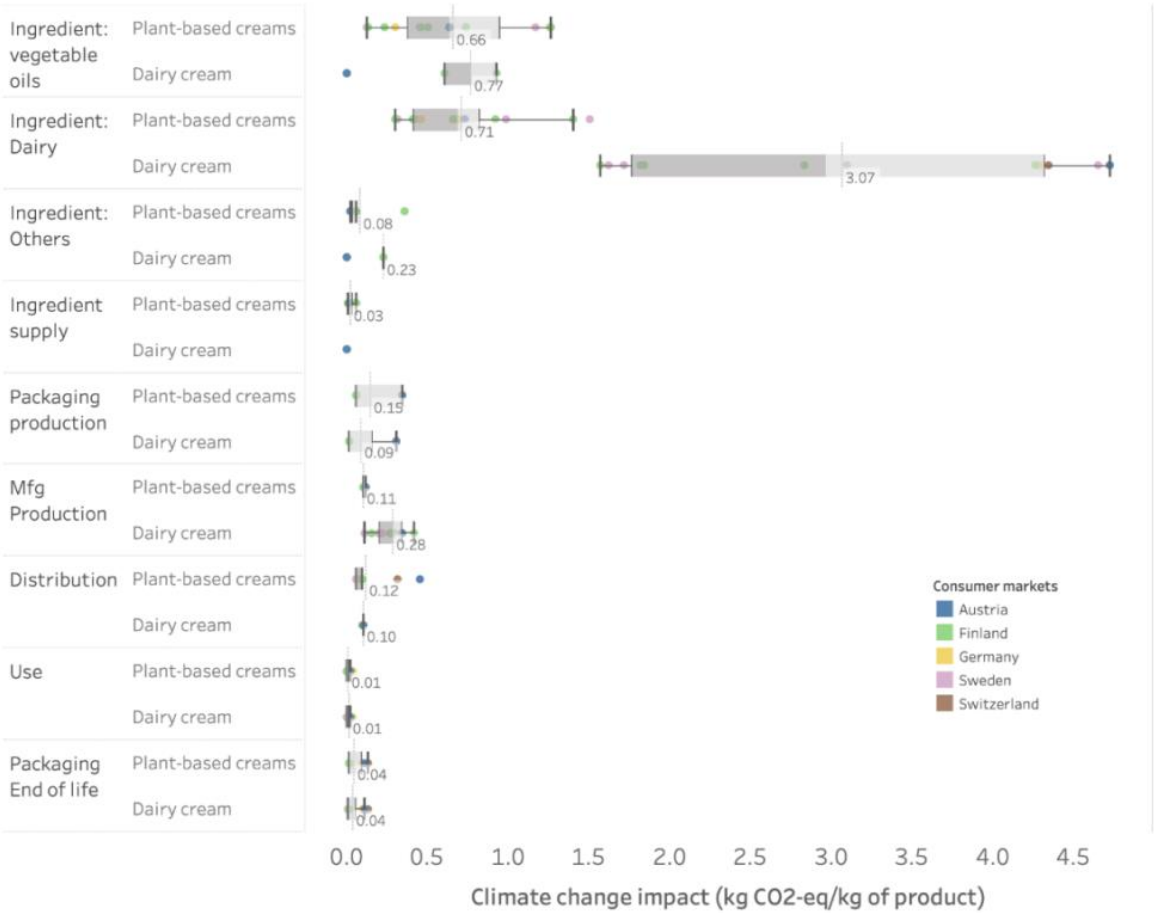

Fig. S7 Impact on climate change of 16 plant-based creams and 12 dairy creams per kg by life cycle stages (the average values are shown in the figure)

S3.7 Life cycle impact assessment results

Table S8-1 gives the life cycle impact results of global warming potential (GWP), Land occupation (LO), Land use (LU), Water consumption (WC) and water scarcity footprint respectively, for the 268 products under evaluation as well as the weighted average for each country the total 21 markets. Table S8-2 gives breakdown of life cycle carbon footprint, measured as GWP, by life cycle stages. Table S8-3 gives further break-down of carbon footprint by farm activities for producing1 kg of raw milk input used by butter production.

Table S8-1 Life cycle impact results for 1 kg of plant-based spreads, cream and butter

Product_ID	Type	Country	GWP	LO	LU	WC	WSF
Unit			kg CO2 eq	m2.y	kg C deficit	m^3	m^3 water-eq
Product1_8740002-AT	PB-spread	Austria	3.41	3.71	59.12	0.043	0.48
Product2_8300023-AT	PB-spread	Austria	2.95	3.77	60.7	0.052	0.56
Product3_8740003-AT	PB-spread	Austria	2.51	2.47	39.1	0.031	0.33
Product4_8626615-AT	PB-spread	Austria	3.96	3.27	29.6	0.083	0.6
Product5_8486594-AT	PB-spread	Austria	1.82	1.75	17.97	0.047	0.26
Product6_9046064-AT	PB-spread	Austria	3.05	2.5	23.54	0.053	0.61
Product7_8583418-AT	PB-spread	Austria	2.44	1.84	16.81	0.043	0.39
Product8_8629141-AT	PB-spread	Austria	3.00	2.64	36.1	0.039	0.46
Product9_120828-AT	PB-spread	Austria	2.64	3.09	30.27	0.083	0.56
Product10_8919936-AT	PB-spread	Austria	5.09	4.43	41.04	0.091	1.11
Product11_8950851-AT	PB-spread	Austria	4.21	3.74	31.4	0.037	0.5
Product12_8630825-AT	PB-spread	Austria	3.66	3.9	37.02	0.103	0.6
Product13_8585225-AT	PB-spread	Austria	3.91	4.01	40.8	0.029	0.28
Product14_8696266-BE	PB-spread	Belgium	5.76	9.06	126.77	0.099	1.11
Product15_8820465-BE	PB-spread	Belgium	4.53	6.52	90.66	0.091	1.05
Product16_8740005-BE	PB-spread	Belgium	2.19	3.16	36.6	0.018	0.24
Product17_8594809-BE	PB-spread	Belgium	2.36	3.19	44.42	0.045	0.5
Product18_8740004-BE	PB-spread	Belgium	2.85	4.15	56.03	0.033	0.4
Product19_8751272-BE	PB-spread	Belgium	3.86	3.6	37.46	0.091	0.84
Product20_8786162-BE	PB-spread	Belgium	3.50	4.43	42.04	0.028	0.38
Product21_8620364-BE	PB-spread	Belgium	2.70	2.96	27.66	0.08	0.64
Product22_8919936-BE	PB-spread	Belgium	4.84	4.45	40.46	0.092	1.17
Product23_83265754-CA	PB-spread	Canada	2.42	8.16	82.88	0.025	0.38
Product24_83246450-CA	PB-spread	Canada	1.51	4.06	41.24	0.017	0.24
Product25_83265755-CA	PB-spread	Canada	2.95	12.78	73.79	1.046	69.85
Product26_83265753-CA	PB-spread	Canada	2.43	8.16	82.89	0.025	0.38
Product27_83246524-CA	PB-spread	Canada	1.55	3.59	47.97	0.017	0.25
Product28_83246481-CA	PB-spread	Canada	2.44	8.17	83.1	0.026	0.39
Product29_83265756-CA	PB-spread	Canada	2.32	8.07	82.17	0.024	0.36
Product30_8740002-CH	PB-spread	Switzerland	3.24	3.7	58.64	0.042	0.47

Product31_8300023-CH	PB-spread	Switzerland	2.77	3.75	60.18	0.051	0.54
Product32_8486594-CH	PB-spread	Switzerland	1.65	1.73	17.48	0.046	0.25
Product33_9046064-CH	PB-spread	Switzerland	2.87	2.48	23.02	0.052	0.59
Product34_8583418-CH	PB-spread	Switzerland	2.24	1.82	16.22	0.042	0.36
Product35_120828-CH	PB-spread	Switzerland	2.42	3.07	29.63	0.082	0.52
Product36_8919936-CH	PB-spread	Switzerland	4.86	4.41	40.35	0.09	1.07
Product37_8950851-CH	PB-spread	Switzerland	4.42	3.74	31.97	0.037	0.5
Product38_8620366-CH	PB-spread	Switzerland	2.92	3.41	32.12	0.089	0.54
Product39_9018021-CZ	PB-spread	Czech Republic	3.68	6.77	75.09	0.03	0.43
Product40_8867358-CZ	PB-spread	Czech Republic	4.43	3.21	27.74	0.034	0.5
Product41_8867833-CZ	PB-spread	Czech Republic	3.81	3.69	30.55	0.035	0.42
Product42_8783427-CZ	PB-spread	Czech Republic	3.49	3.36	27.82	0.032	0.38
Product43_8724230-CZ	PB-spread	Czech Republic	1.87	2.55	23.79	0.018	0.18
Product44_8675323-CZ	PB-spread	Czech Republic	1.24	1.18	10.97	0.013	0.12
Product45_8735122-CZ	PB-spread	Czech Republic	1.80	2.41	22.51	0.017	0.15
Product46_9190688-CZ	PB-spread	Czech Republic	2.62	3.53	32.35	0.023	0.23
Product47_9233728-CZ	PB-spread	Czech Republic	2.48	3.87	36.32	0.022	0.22
Product48_8695998-CZ	PB-spread	Czech Republic	2.23	3.38	35.12	0.02	0.25
Product49_9233727-CZ	PB-spread	Czech Republic	3.35	2.87	24.16	0.031	0.41
Product50_8919936-CZ	PB-spread	Czech Republic	4.85	4.89	44.1	0.047	0.84
Product51_9226791-CZ	PB-spread	Czech Republic	4.21	3.78	31.74	0.038	0.51
Product52_9164153-DE	PB-spread	Germany	2.98	2.88	28.82	0.021	0.46
Product53_8740002-DE	PB-spread	Germany	3.08	3.7	58.24	0.042	0.48
Product54_8300023-DE	PB-spread	Germany	2.67	3.77	59.99	0.052	0.59
Product55_9171823-DE	PB-spread	Germany	3.80	6.58	74.09	0.03	0.48
Product56_8740003-DE	PB-spread	Germany	2.20	2.46	38.26	0.03	0.34
Product57_8728975-DE	PB-spread	Germany	1.75	2.63	19.31	0.074	2.17
Product58_8486594-DE	PB-spread	Germany	1.50	1.74	17.15	0.047	0.28
Product59_9046064-DE	PB-spread	Germany	2.77	2.5	22.84	0.053	0.64
Product60_8583418-DE	PB-spread	Germany	2.23	1.85	16.37	0.044	0.46
Product61_8626611-DE	PB-spread	Germany	2.20	1.8	15.98	0.045	0.41
Product62_8704756-DE	PB-spread	Germany	2.20	2.84	28.86	0.019	0.23
Product63_120828-DE	PB-spread	Germany	2.48	3.11	29.99	0.085	0.65
Product64_8919936-DE	PB-spread	Germany	4.98	4.46	40.89	0.093	1.22
Product65_8950851-DE	PB-spread	Germany	4.44	3.77	32.16	0.039	0.56
Product66_8620366-DE	PB-spread	Germany	3.21	3.54	33.71	0.09	0.65
Product67_9190688-DE	PB-spread	Germany	3.02	3.58	33.69	0.026	0.37
Product68_8626615-DE	PB-spread	Germany	4.11	3.35	30.49	0.09	0.85
Product69_8898753-DK	PB-spread	Denmark	3.07	6.71	73.6	0.098	1.03
Product70_8749609-DK	PB-spread	Denmark	2.73	3.39	47.96	0.064	0.64
Product71_8933408-DK	PB-spread	Denmark	4.01	7.43	98.59	0.12	1.08
Product72_8592204-DK	PB-spread	Denmark	2.67	1.76	16.2	0.048	0.47

Product73_1106130-ES	PB-spread	Spain	2.76	2.18	23.77	0.034	0.42
Product74_9138810-ES	PB-spread	Spain	5.45	6.27	86.06	0.103	1.27
Product75_9105568-ES	PB-spread	Spain	4.76	7.04	79.46	0.032	0.43
Product76_8500332-ES	PB-spread	Spain	4.99	6.96	102.45	0.077	0.87
Product77_8125138-ES	PB-spread	Spain	2.82	4.07	49.64	0.06	2.37
Product78_8626605-ES	PB-spread	Spain	4.34	6.52	99.53	0.053	0.68
Product79_9235692-ES	PB-spread	Spain	4.83	6	86.77	0.103	1.14
Product80_8585188-ES	PB-spread	Spain	3.15	3.59	59.43	0.043	0.55
Product81_1106141-ES	PB-spread	Spain	3.32	4.52	67.62	0.018	0.33
Product82_8849316-ES	PB-spread	Spain	4.88	6.26	89.62	0.065	0.73
Product83_8620328-ES	PB-spread	Spain	4.99	4.83	88.48	0.079	0.89
Product84_8898753-FI	PB-spread	Finland	3.12	6.75	74.01	0.099	1.03
Product85_9168816-FI	PB-spread	Finland	1.76	3.87	43.46	0.054	0.55
Product86_1001483-FI	PB-spread	Finland	2.51	6.06	67.06	0.082	0.84
Product87_8933408-FI	PB-spread	Finland	4.06	7.47	99.01	0.121	1.08
Product88_9171823-FI	PB-spread	Finland	3.79	6.6	74.17	0.029	0.4
Product89_9138901-FI	PB-spread	Finland	5.16	6.23	83.93	0.104	1.26
Product90_8919936-FI	PB-spread	Finland	4.99	4.59	42.57	0.076	1.03
Product91_8933389-FI	PB-spread	Finland	2.83	6.02	63.44	0.075	0.48
Product92_9057036-FI	PB-spread	Finland	4.20	6.82	74.63	0.164	1.21
Product93_8680037-FI	PB-spread	Finland	3.52	3.65	31.04	0.027	0.27
Product94_8854468-FI	PB-spread	Finland	2.64	2.66	23.26	0.02	0.19
Product95_8588111-FI	PB-spread	Finland	1.85	2.87	29.83	0.029	0.32
Product96_8587428-FI	PB-spread	Finland	2.43	3.53	33.53	0.017	0.2
Product97_8623213-FI	PB-spread	Finland	1.59	1.54	15.04	0.015	0.17
Product98_8592204-FI	PB-spread	Finland	1.93	1.99	18.45	0.016	0.16
Product99_9171823-FR	PB-spread	France	4.04	6.59	74.91	0.031	0.48
Product100_8716407-FR	PB-spread	France	4.02	5.12	72.87	0.09	1.03
Product101_8716422-FR	PB-spread	France	3.30	4.49	61.98	0.064	0.67
Product102_8939673-FR	PB-spread	France	3.84	5.77	84.49	0.067	0.76
Product103_8716972-FR	PB-spread	France	2.62	3.43	53.64	0.045	0.52
Product104_9114666-FR	PB-spread	France	4.60	6.02	85.27	0.105	1.21
Product105_8941210-FR	PB-spread	France	3.68	2.58	22.96	0.066	0.71
Product106_8919936-GR	PB-spread	Greece	5.90	4.72	45.27	0.073	1.13
Product107_8800658-GR	PB-spread	Greece	3.78	3.8	36.97	0.03	0.49
Product108_1031196-GR	PB-spread	Greece	5.93	5.07	47.31	0.053	1.09
Product109_8630227-GR	PB-spread	Greece	2.87	3.69	37.54	0.083	0.76
Product110_8751710-GR	PB-spread	Greece	2.13	2.59	29.73	0.048	0.49
Product111_8564454-GR	PB-spread	Greece	4.72	2.19	21.93	0.055	0.95
Product112_8715874-GR	PB-spread	Greece	3.13	3.92	39.79	0.086	0.84
Product113_9018021-HU	PB-spread	Hungary	3.75	6.78	75.45	0.031	0.47
Product114_8675323-HU	PB-spread	Hungary	1.08	1.52	16.21	0.012	0.11

Product115_8756278-HU	PB-spread	Hungary	1.86	2.51	23.72	0.017	0.19
Product116_8867358-HU	PB-spread	Hungary	4.20	3.69	31.46	0.038	0.55
Product117_9190688-HU	PB-spread	Hungary	2.72	3.55	32.83	0.024	0.28
Product118_8867833-HU	PB-spread	Hungary	4.04	3.73	31.47	0.037	0.53
Product119_9233728-HU	PB-spread	Hungary	2.51	3.88	36.55	0.022	0.24
Product120_8856605-HU	PB-spread	Hungary	3.58	4.01	39.97	0.032	0.41
Product121_9236827-HU	PB-spread	Hungary	2.87	3.12	31.08	0.085	0.62
Product122_8919936-HU	PB-spread	Hungary	4.95	4.9	44.52	0.047	0.88
Product123_9226791-HU	PB-spread	Hungary	4.25	3.79	31.98	0.038	0.53
Product124_8914273-IE	PB-spread	Ireland	4.92	5.46	32.5	0.126	5.94
Product125_8518006-IE	PB-spread	Ireland	2.47	4.86	32	0.082	5.15
Product126_8518082-IE	PB-spread	Ireland	3.68	6.64	82.41	0.067	0.76
Product127_8588122-IE	PB-spread	Ireland	2.56	2.92	27.52	0.077	0.54
Product128_9019796-IE	PB-spread	Ireland	5.88	6.04	72.48	0.073	1.19
Product129_8740001-IE	PB-spread	Ireland	1.88	2.98	38.22	0.039	0.42
Product130_8954218-IE	PB-spread	Ireland	2.68	4.4	56.69	0.056	0.61
Product131_8939673-IE	PB-spread	Ireland	3.28	5.89	81.7	0.057	0.64
Product132_8517980-IE	PB-spread	Ireland	2.19	3.47	52.21	0.044	0.49
Product133_8518007-IE	PB-spread	Ireland	2.08	3.53	44	0.052	1.99
Product134_9171823-NL	PB-spread	Netherlands	3.41	6.55	72.66	0.028	0.42
Product135_8820465-NL	PB-spread	Netherlands	4.49	6.52	90.51	0.091	1.05
Product136_8740005-NL	PB-spread	Netherlands	1.68	3.06	35.29	0.018	0.22
Product137_9138809-NL	PB-spread	Netherlands	4.91	6.21	82.78	0.104	1.3
Product138_8594809-NL	PB-spread	Netherlands	2.33	3.18	44.29	0.045	0.49
Product139_8740004-NL	PB-spread	Netherlands	2.78	3.9	56.62	0.037	0.43
Product140_8629141-NL	PB-spread	Netherlands	2.47	2.93	38.12	0.05	0.55
Product141_8629137-NL	PB-spread	Netherlands	2.51	2.97	37.76	0.052	0.55
Product142_8637225-NL	PB-spread	Netherlands	2.41	2.63	37.81	0.056	0.55
Product143_8751272-NL	PB-spread	Netherlands	3.85	3.6	37.36	0.091	0.83
Product144_8919936-NL	PB-spread	Netherlands	4.86	4.43	40.18	0.091	1.16
Product145_9106654-PL	PB-spread	Poland	2.14	2.63	23.95	0.025	0.3
Product146_8867358-PL	PB-spread	Poland	3.97	3.62	30.09	0.039	0.49
Product147_8867833-PL	PB-spread	Poland	3.73	3.71	30.39	0.038	0.46
Product148_8783427-PL	PB-spread	Poland	3.40	3.38	27.63	0.035	0.42
Product149_9190688-PL	PB-spread	Poland	2.48	3.54	32.01	0.026	0.25
Product150_9233727-PL	PB-spread	Poland	3.18	2.88	23.71	0.033	0.41
Product151_9233728-PL	PB-spread	Poland	2.31	3.88	35.88	0.024	0.22
Product152_8919936-PL	PB-spread	Poland	4.72	4.9	43.74	0.049	0.86
Product153_8500332-PT	PB-spread	Portugal	5.02	7.01	102.72	0.08	1.01
Product154_8473731-PT	PB-spread	Portugal	4.19	5.82	85.8	0.069	0.83
Product155_8626608-PT	PB-spread	Portugal	3.32	3.43	56.58	0.049	0.61
Product156_9091992-PT	PB-spread	Portugal	2.96	3.37	41.35	0.124	1.2

Product157_8710390-PT	PB-spread	Portugal	5.15	6.35	90.39	0.075	1.02
Product158_8761848-PT	PB-spread	Portugal	4.45	1.92	15.53	0.052	1.01
Product159_8867358-RO	PB-spread	Romania	4.25	3.64	31.29	0.035	0.39
Product160_8724230-RO	PB-spread	Romania	2.24	2.55	24.9	0.018	0.19
Product161_8294470-RO	PB-spread	Romania	1.06	1.51	16.11	0.012	0.09
Product162_9233727-RO	PB-spread	Romania	3.73	2.88	25.32	0.032	0.42
Product163_9233728-RO	PB-spread	Romania	2.85	3.88	37.46	0.023	0.23
Product164_9190688-RO	PB-spread	Romania	2.96	3.53	33.36	0.024	0.22
Product165_8856605-RO	PB-spread	Romania	3.31	3.95	38.93	0.028	0.25
Product166_9226791-RO	PB-spread	Romania	4.58	3.79	32.88	0.039	0.52
Product167_8898753-SE	PB-spread	Sweden	3.00	6.7	73.42	0.097	0.98
Product168_9168816-SE	PB-spread	Sweden	1.70	3.84	43.1	0.053	0.53
Product169_9138901-SE	PB-spread	Sweden	5.01	6.18	83.25	0.101	1.2
Product170_8933408-SE	PB-spread	Sweden	4.03	7.44	98.76	0.12	1.08
Product171_9171823-SE	PB-spread	Sweden	3.68	6.56	73.58	0.027	0.35
Product172_8919936-SE	PB-spread	Sweden	4.69	4.64	42.88	0.06	0.87
Product173_8854468-SE	PB-spread	Sweden	2.57	2.63	22.88	0.019	0.17
Product174_8680037-SE	PB-spread	Sweden	3.45	3.62	30.62	0.025	0.25
Product175_9213754-SE	PB-spread	Sweden	2.13	3.42	32.42	0.013	0.11
Product176_8623213-SE	PB-spread	Sweden	1.55	1.5	14.74	0.014	0.16
Product177_8592204-SE	PB-spread	Sweden	1.88	1.96	18.12	0.015	0.15
Product178_8933389-SE	PB-spread	Sweden	2.81	5.99	63.19	0.075	0.48
Product179_9155140-SE	PB-spread	Sweden	4.92	4.84	43.6	0.046	0.82
Product180_9057036-SE	PB-spread	Sweden	4.18	6.8	74.38	0.163	1.21
Product181_9049971-SE	PB-spread	Sweden	3.21	3.3	27.51	0.026	0.24
Product182_9018021-SK	PB-spread	Slovakia	3.57	6.75	74.78	0.029	0.39
Product183_8867358-SK	PB-spread	Slovakia	3.60	3.14	25.24	0.028	0.32
Product184_8867833-SK	PB-spread	Slovakia	3.50	3.63	29.51	0.031	0.27
Product185_8783427-SK	PB-spread	Slovakia	3.20	3.31	26.87	0.028	0.24
Product186_8724230-SK	PB-spread	Slovakia	1.78	2.54	23.57	0.017	0.14
Product187_8675323-SK	PB-spread	Slovakia	1.17	1.17	10.82	0.013	0.09
Product188_8735122-SK	PB-spread	Slovakia	1.70	2.4	22.26	0.016	0.11
Product189_9233728-SK	PB-spread	Slovakia	2.41	3.86	36.18	0.021	0.2
Product190_8695998-SK	PB-spread	Slovakia	2.14	3.37	34.89	0.02	0.21
Product191_9233727-SK	PB-spread	Slovakia	3.28	2.86	24.05	0.031	0.39
Product192_8919936-SK	PB-spread	Slovakia	4.73	4.87	43.74	0.045	0.79
Product193_8518008-UK	PB-spread	United Kingdom	1.70	3.14	17.47	0.063	3.97
Product194_8914273-UK	PB-spread	United Kingdom	4.85	5.45	32.25	0.125	5.9
Product195_8518006-UK	PB-spread	United Kingdom	2.44	4.85	31.86	0.081	5.13
Product196_8518082-UK	PB-spread	United Kingdom	3.64	6.63	82.26	0.066	0.73
Product197_8588122-UK	PB-spread	United Kingdom	2.48	2.91	27.22	0.076	0.49
Product198_9019796-UK	PB-spread	United Kingdom	5.81	6.03	72.23	0.072	1.15

Product199_8740001-UK	PB-spread	United Kingdom	1.87	2.98	38.16	0.039	0.41
Product200_8954218-UK	PB-spread	United Kingdom	2.65	4.4	56.58	0.056	0.59
Product201_8939673-UK	PB-spread	United Kingdom	3.25	5.88	81.59	0.056	0.62
Product202_8517980-UK	PB-spread	United Kingdom	2.17	3.47	52.15	0.044	0.48
Product203_8518007-UK	PB-spread	United Kingdom	2.07	3.52	43.94	0.052	1.98
Product204_84146485-US	PB-spread	United States	2.79	2.68	27.19	0.021	0.45
Product205_84146516-US	PB-spread	United States	2.77	2.61	26.45	0.021	0.46
Product206_84146529-US	PB-spread	United States	2.40	2.08	21.23	0.018	0.38
Product207_84147017-US	PB-spread	United States	2.98	2.88	28.82	0.021	0.48
Product208_84117084-US	PB-spread	United States	4.59	5.3	50.27	0.037	0.71
Product209_84137908-US	PB-spread	United States	3.22	3.22	32.02	0.023	0.52
Product210_84138021-US	PB-spread	United States	2.47	2.25	23.01	0.018	0.39
Product211_84139794-US	PB-spread	United States	3.66	3.32	31.35	0.029	0.59
Product212_84107197-US	PB-spread	United States	4.73	5.27	50.27	0.037	0.72
Product213_7803432-AT	PB-cream	Austria	2.43	1.36	12.85	0.031	0.45
Product214_7803432-CH	PB-cream	Switzerland	2.29	1.36	12.43	0.03	0.44
Product215_8225266-DE	PB-cream	Germany	1.50	0.82	7.27	0.019	0.3
Product216_7803432-DE	PB-cream	Germany	2.06	1.35	11.84	0.03	0.43
Product217_9016504-DE	PB-cream	Germany	2.73	2.05	13.21	0.054	0.87
Product218_2019002-FI	PB-cream	Finland	1.11	1.14	11.59	0.011	0.22
Product219_8292148-FI	PB-cream	Finland	0.85	0.74	8.24	0.01	0.24
Product220_8631323-FI	PB-cream	Finland	2.23	2.67	19.31	0.059	0.73
Product221_9144844-FI	PB-cream	Finland	0.96	0.88	9.34	0.011	0.24
Product222_1000949-FI	PB-cream	Finland	2.76	3.14	22.46	0.095	1.73
Product223_2019204-FI	PB-cream	Finland	1.75	2.66	24.27	0.036	0.83
Product224_2019002-SE	PB-cream	Sweden	1.07	1.14	11.63	0.01	0.18
Product225_8292148-SE	PB-cream	Sweden	0.81	0.75	8.36	0.009	0.18
Product226_8631323-SE	PB-cream	Sweden	2.19	2.68	19.51	0.057	0.66
Product227_1000949-SE	PB-cream	Sweden	2.80	3.21	24.5	0.086	1.3
Product228_2019001-SE	PB-cream	Sweden	2.42	3.84	26.27	0.1	1.19
Product229_Dairy spread_75% fat-DK	Dairy spread	Denmark	9.36	7.9	71.13	0.151	4.68
Product230_Dairy spread_40% fat-FI	Dairy spread	Finland	5.68	5.01	40.66	0.121	4.19
Product231_Dairy spread_60% fat-FI	Dairy spread	Finland	7.58	6.9	55.96	0.163	5.75
Product232_Dairy spread_75% fat-FI	Dairy spread	Finland	8.96	8.31	67.33	0.195	6.89
Product233_Dairy spread_40% fat-SE	Dairy spread	Sweden	6.02	5.26	49.19	0.083	2.55
Product234_Dairy spread_60% fat-SE	Dairy spread	Sweden	8.05	7.26	67.8	0.112	3.47
Product235_Dairy spread_75% fat-SE	Dairy spread	Sweden	9.53	8.74	81.65	0.133	4.15
Product236_Cream_30% fat-AT	Dairy cream	Austria	5.62	4.59	39.68	0.045	1.28
Product237_Cream_30% fat-CH	Dairy cream	Switzerland	5.17	4.28	36.07	0.059	1.93
Product238_Cream_30% fat-DE	Dairy cream	Germany	5.25	3.99	35.32	0.051	1.62

Product239_Cream_15% fat-FI	Dairy cream	Finland	1.88	1.72	13.87	0.038	1.37
Product240_Cream_27% fat-FI	Dairy cream	Finland	3.27	3.03	24.61	0.067	2.46
Product241_Cream_40% fat-FI	Dairy cream	Finland	4.83	4.52	36.76	0.101	3.69
Product242_Cream_15% fat-SE	Dairy cream	Sweden	1.96	1.8	16.68	0.025	0.82
Product243_Cream_27% fat-SE	Dairy cream	Sweden	3.43	3.19	29.68	0.045	1.47
Product244_Cream_40% fat-SE	Dairy cream	Sweden	5.09	4.76	44.4	0.067	2.2
Product245_Vanilla whip-001_FI	Dairy cream	Finland	3.18	3.4	23.26	0.098	1.65
Product246_Vanilla whip-002_FI	Dairy cream	Finland	3.47	2.31	18.47	0.06	1.42
Product247_Vanilla whip_003-SE	Dairy cream	Sweden	2.20	1.85	16.65	0.046	1.08
Product248_Butter-AT	Dairy Butter	Austria	13.64	12.4	105.63	0.12	3.3
Product249_Butter-BE	Dairy Butter	Belgium	12.74	11.43	102.02	0.118	3.44
Product250_Butter-CA	Dairy Butter	Canada	11.06	11.14	90.21	0.328	11.88
Product251_Butter-CH	Dairy Butter	Switzerland	12.38	11.53	95.85	0.156	5.05
Product252_Butter-CZ	Dairy Butter	Czech Republic	11.96	10.44	93.96	0.122	3.19
Product253_Butter-DE	Dairy Butter	Germany	12.68	10.76	93.82	0.135	4.22
Product254_Butter-DK	Dairy Butter	Denmark	9.87	8.7	78.21	0.164	5.11
Product255_Butter-ES	Dairy Butter	Spain	14.47	13.93	132.57	0.099	2.75
Product256_Butter-FI	Dairy Butter	Finland	9.45	9.14	73.98	0.212	7.55
Product257_Butter-FR	Dairy Butter	France	12.28	11.17	96.6	0.091	2.33
Product258_Butter-GR	Dairy Butter	Greece	14.20	12.9	117.31	0.152	5.23
Product259_Butter-HU	Dairy Butter	Hungary	10.43	9.79	75.44	0.098	2.78
Product260_Butter-IE	Dairy Butter	Ireland	11.77	13.34	90.33	0.049	0.87
Product261_Butter-NL	Dairy Butter	Netherlands	12.23	9.87	89.23	0.111	3.08
Product262_Butter-PL	Dairy Butter	Poland	13.12	20.11	126.72	0.095	1.51
Product263_Butter-PT	Dairy Butter	Portugal	14.47	15.88	140.41	0.109	2.95
Product264_Butter-RO	Dairy Butter	Romania	10.86	25.5	152.13	0.06	1.19
Product265_Butter-SE	Dairy Butter	Sweden	10.07	9.64	89.81	0.145	4.53
Product266_Butter-SK	Dairy Butter	Slovakia	12.06	15.01	116.26	0.117	2.94
Product267_Butter-UK	Dairy Butter	United Kingdom	12.37	10.6	91.75	0.103	2.97
Product268_Butter-US	Dairy Butter	United States	12.05	11.77	102.09	0.243	8.99
Weighted average results for each country and the 21 markets							
WeightedAve*_PB-spread_AT	PB-spread	Austria	3.66	3.59	37.25	0.059	0.54
WeightedAve_PB-spread_BE	PB-spread	Belgium	3.61	4.72	58.53	0.063	0.7
WeightedAve_PB-spread_CA	PB-spread	Canada	2.23	7.57	70.58	0.169	10.27
WeightedAve_PB-spread_CH	PB-spread	Switzerland	2.93	2.98	32.79	0.057	0.52
WeightedAve_PB-spread_CZ	PB-spread	Czech Republic	3.23	3.63	33.61	0.029	0.37
WeightedAve_PB-spread_DE	PB-spread	Germany	2.96	2.97	28.49	0.056	0.59
WeightedAve_PB-spread_DK	PB-spread	Denmark	3.05	4.38	52.92	0.077	0.76
WeightedAve_PB-spread_ES	PB-spread	Spain	4.57	5.4	82.51	0.066	0.83
WeightedAve_PB-spread_FI	PB-spread	Finland	3.20	4.84	52.46	0.064	0.63
WeightedAve_PB-spread_FR	PB-spread	France	3.71	3.74	44.44	0.066	0.74
WeightedAve_PB-spread_GR	PB-spread	Greece	3.43	3.26	33.45	0.066	0.77
WeightedAve_PB-spread_HU	PB-spread	Hungary	2.96	3.3	30.78	0.032	0.39
WeightedAve_PB-spread_IE	PB-spread	Ireland	3.06	4.51	55.84	0.06	1.03
WeightedAve_PB-spread_NL	PB-spread	Netherlands	3.24	4.05	50.09	0.061	0.69
WeightedAve_PB-spread_PL	PB-spread	Poland	2.78	3.15	27.6	0.03	0.37
WeightedAve_PB-spread_PT	PB-spread	Portugal	4.20	4.08	53.84	0.078	1.02
WeightedAve_PB-spread_RO	PB-spread	Romania	2.37	2.62	25.29	0.021	0.21
WeightedAve_PB-spread_SE	PB-spread	Sweden	2.91	3.84	39.57	0.046	0.46
WeightedAve_PB-spread_SK	PB-spread	Slovakia	3.01	3.3	29.02	0.027	0.31
WeightedAve_PB-spread_UK	PB-spread	United Kingdom	2.99	4.48	48.17	0.067	2.03
WeightedAve_PB-spread_US	PB-spread	United States	3.09	2.93	28.77	0.023	0.5
WeightedAve_PB-spread_GLO	PB-spread	21 markets	3.14	3.73	40.5	0.054	1.05
WeightedAve_Butter_GLO	Dairy Butter	21 markets	12.10	11.89	97.96	0.153	4.95

Note : WeightedAve* : The country weighted average results for PB-spread are calculated based on market share of different product, obtained per communication with Upfield. The global weighted average results of 21 markets for PB-Spread and Dairy butter are calculated by multiplying the weighted country average carbon footprint by the market share derived from the 2018 butter production data (Eurostat[1], USDA[2] and Canadian Dairy Information Center[3]) for respective countries.

[1]Eurostat https://ec.europa.eu/eurostat/databrowser/view/tag00038/default/table?lang=en (accessed January 31st, 20202)

[2]USDA https://www.ers.usda.gov/webdocs/DataFiles/48685/Dairyglance.xlsx?v=1337.1 (accessed January 31st, 20202)

[3]Canadian Dairy Information Center https://aimis-simia-cdic-ccil.agr.gc.ca/rp/index-eng.cfm?action=pR&pdctc=&r=261#wb-cont

Table S8-2 Carbon footprint (kg CO_2-eq) break-down by stages for 1 kg of plant-based spreads, cream and butter

Product_ID	Type	Market	Total	Ingredient	Mfg Production	Ingredient supply and product distribution	Use	Packaging and its end of life
Product1_8740002-AT	PB-spread	Austria	3.41	2.41	0.05	0.59	0.04	0.31
Product2_8300023-AT	PB-spread	Austria	2.95	1.96	0.05	0.58	0.04	0.31
Product3_8740003-AT	PB-spread	Austria	2.51	1.54	0.05	0.56	0.04	0.31
Product4_8626615-AT	PB-spread	Austria	3.96	3.00	0.05	0.55	0.04	0.31
Product5_8486594-AT	PB-spread	Austria	1.82	0.87	0.05	0.53	0.04	0.31
Product6_9046064-AT	PB-spread	Austria	3.05	2.10	0.05	0.54	0.04	0.31
Product7_8583418-AT	PB-spread	Austria	2.44	1.49	0.05	0.54	0.04	0.31
Product8_8629141-AT	PB-spread	Austria	3.00	2.02	0.05	0.57	0.04	0.31
Product9_120828-AT	PB-spread	Austria	2.64	1.80	0.05	0.55	0.04	0.20
Product10_8919936-AT	PB-spread	Austria	5.09	4.14	0.05	0.55	0.04	0.31
Product11_8950851-AT	PB-spread	Austria	4.21	3.45	0.04	0.36	0.04	0.31
Product12_8630825-AT	PB-spread	Austria	3.66	2.71	0.05	0.55	0.04	0.31
Product13_8585225-AT	PB-spread	Austria	3.91	2.88	0.03	0.65	0.04	0.31
Product14_8696266-BE	PB-spread	Belgium	5.76	5.09	0.05	0.27	0.03	0.32
Product15_8820465-BE	PB-spread	Belgium	4.53	3.90	0.05	0.23	0.03	0.32
Product16_8740005-BE	PB-spread	Belgium	2.19	1.18	0.04	0.62	0.03	0.32
Product17_8594809-BE	PB-spread	Belgium	2.36	1.79	0.05	0.17	0.03	0.32
Product18_8740004-BE	PB-spread	Belgium	2.85	2.13	0.05	0.32	0.03	0.32
Product19_8751272-BE	PB-spread	Belgium	3.86	3.51	0.05	0.17	0.03	0.10
Product20_8786162-BE	PB-spread	Belgium	3.50	2.50	0.04	0.61	0.03	0.32
Product21_8620364-BE	PB-spread	Belgium	2.70	2.15	0.05	0.14	0.03	0.32
Product22_8919936-BE	PB-spread	Belgium	4.84	4.29	0.05	0.15	0.03	0.31
Product23_83265754-CA	PB-spread	Canada	2.42	1.91	0.06	0.19	0.03	0.23
Product24_83246450-CA	PB-spread	Canada	1.51	1.02	0.06	0.18	0.03	0.23
Product25_83265755-CA	PB-spread	Canada	2.95	2.43	0.06	0.19	0.03	0.23
Product26_83265753-CA	PB-spread	Canada	2.43	1.91	0.06	0.19	0.03	0.23
Product27_83246524-CA	PB-spread	Canada	1.55	1.04	0.06	0.18	0.03	0.23
Product28_83246481-CA	PB-spread	Canada	2.44	1.93	0.06	0.19	0.03	0.23
Product29_83265756-CA	PB-spread	Canada	2.32	1.81	0.06	0.19	0.03	0.23
Product30_8740002-CH	PB-spread	Switzerland	3.24	2.40	0.05	0.45	0.01	0.33
Product31_8300023-CH	PB-spread	Switzerland	2.77	1.93	0.05	0.44	0.01	0.33
Product32_8486594-CH	PB-spread	Switzerland	1.65	0.86	0.05	0.40	0.01	0.33
Product33_9046064-CH	PB-spread	Switzerland	2.87	2.08	0.05	0.40	0.01	0.33
Product34_8583418-CH	PB-spread	Switzerland	2.24	1.44	0.05	0.40	0.01	0.33
Product35_120828-CH	PB-spread	Switzerland	2.42	1.74	0.05	0.41	0.01	0.21
Product36_8919936-CH	PB-spread	Switzerland	4.86	4.07	0.05	0.41	0.01	0.31

Product37_8950851-CH	PB-spread	Switzerland	4.42	3.42	0.04	0.61	0.01	0.33
Product38_8620366-CH	PB-spread	Switzerland	2.92	2.24	0.05	0.40	0.01	0.21
Product39_9018021-CZ	PB-spread	Czech Republic	3.68	2.94	0.04	0.34	0.09	0.27
Product40_8867358-CZ	PB-spread	Czech Republic	4.43	3.34	0.14	0.59	0.09	0.27
Product41_8867833-CZ	PB-spread	Czech Republic	3.81	3.28	0.04	0.29	0.09	0.10
Product42_8783427-CZ	PB-spread	Czech Republic	3.49	2.97	0.04	0.29	0.09	0.10
Product43_8724230-CZ	PB-spread	Czech Republic	1.87	1.27	0.04	0.27	0.09	0.19
Product44_8675323-CZ	PB-spread	Czech Republic	1.24	0.66	0.04	0.26	0.09	0.19
Product45_8735122-CZ	PB-spread	Czech Republic	1.80	1.20	0.04	0.27	0.09	0.19
Product46_9190688-CZ	PB-spread	Czech Republic	2.62	1.94	0.04	0.28	0.09	0.27
Product47_9233728-CZ	PB-spread	Czech Republic	2.48	1.79	0.04	0.29	0.09	0.27
Product48_8695998-CZ	PB-spread	Czech Republic	2.23	1.54	0.04	0.29	0.09	0.27
Product49_9233727-CZ	PB-spread	Czech Republic	3.35	2.63	0.04	0.31	0.09	0.27
Product50_8919936-CZ	PB-spread	Czech Republic	4.85	4.10	0.04	0.30	0.09	0.31
Product51_9226791-CZ	PB-spread	Czech Republic	4.21	3.48	0.04	0.33	0.09	0.27
Product52_9164153-DE	PB-spread	Germany	2.98	1.92	0.08	0.69	0.08	0.21
Product53_8740002-DE	PB-spread	Germany	3.08	2.46	0.05	0.21	0.07	0.29
Product54_8300023-DE	PB-spread	Germany	2.67	2.05	0.05	0.20	0.07	0.29
Product55_9171823-DE	PB-spread	Germany	3.80	2.91	0.04	0.49	0.07	0.29
Product56_8740003-DE	PB-spread	Germany	2.20	1.60	0.05	0.18	0.07	0.29
Product57_8728975-DE	PB-spread	Germany	1.75	1.16	0.05	0.17	0.07	0.29
Product58_8486594-DE	PB-spread	Germany	1.50	0.93	0.05	0.16	0.07	0.29
Product59_9046064-DE	PB-spread	Germany	2.77	2.19	0.05	0.16	0.07	0.29
Product60_8583418-DE	PB-spread	Germany	2.23	1.65	0.05	0.16	0.07	0.29
Product61_8626611-DE	PB-spread	Germany	2.20	1.62	0.05	0.16	0.07	0.29
Product62_8704756-DE	PB-spread	Germany	2.20	1.47	0.04	0.44	0.07	0.18
Product63_120828-DE	PB-spread	Germany	2.48	2.00	0.05	0.17	0.07	0.18
Product64_8919936-DE	PB-spread	Germany	4.98	4.38	0.05	0.17	0.07	0.31
Product65_8950851-DE	PB-spread	Germany	4.44	3.55	0.04	0.48	0.07	0.29
Product66_8620366-DE	PB-spread	Germany	3.21	2.70	0.05	0.20	0.07	0.18
Product67_9190688-DE	PB-spread	Germany	3.02	2.19	0.04	0.43	0.07	0.29
Product68_8626615-DE	PB-spread	Germany	4.11	3.52	0.05	0.17	0.07	0.29
Product69_8898753-DK	PB-spread	Denmark	3.07	2.61	0.10	0.06	0.04	0.26
Product70_8749609-DK	PB-spread	Denmark	2.73	1.77	0.05	0.57	0.04	0.30
Product71_8933408-DK	PB-spread	Denmark	4.01	3.08	0.05	0.55	0.04	0.29
Product72_8592204-DK	PB-spread	Denmark	2.67	1.74	0.05	0.53	0.04	0.30
Product73_1106130-ES	PB-spread	Spain	2.76	2.11	0.06	0.28	0.05	0.27
Product74_9138810-ES	PB-spread	Spain	5.45	4.09	0.05	0.95	0.05	0.31
Product75_9105568-ES	PB-spread	Spain	4.76	3.16	0.04	1.40	0.05	0.10
Product76_8500332-ES	PB-spread	Spain	4.99	4.20	0.11	0.36	0.05	0.27
Product77_8125138-ES	PB-spread	Spain	2.82	2.16	0.06	0.27	0.05	0.27

Product78_8626605-ES	PB-spread	Spain	4.34	3.68	0.06	0.28	0.05	0.27
Product79_9235692-ES	PB-spread	Spain	4.83	3.46	0.05	0.96	0.05	0.31
Product80_8585188-ES	PB-spread	Spain	3.15	1.85	0.05	0.92	0.05	0.27
Product81_1106141-ES	PB-spread	Spain	3.32	2.67	0.06	0.27	0.05	0.27
Product82_8849316-ES	PB-spread	Spain	4.88	4.09	0.11	0.36	0.05	0.27
Product83_8620328-ES	PB-spread	Spain	4.99	4.32	0.06	0.29	0.05	0.27
Product84_8898753-FI	PB-spread	Finland	3.12	2.61	0.10	0.13	0.03	0.25
Product85_9168816-FI	PB-spread	Finland	1.76	1.26	0.10	0.12	0.03	0.25
Product86_1001483-FI	PB-spread	Finland	2.51	2.00	0.10	0.13	0.03	0.25
Product87_8933408-FI	PB-spread	Finland	4.06	3.08	0.05	0.62	0.03	0.27
Product88_9171823-FI	PB-spread	Finland	3.79	2.75	0.04	0.66	0.03	0.31
Product89_9138901-FI	PB-spread	Finland	5.16	4.15	0.05	0.67	0.03	0.25
Product90_8919936-FI	PB-spread	Finland	4.99	4.12	0.07	0.46	0.03	0.31
Product91_8933389-FI	PB-spread	Finland	2.83	1.87	0.05	0.62	0.03	0.27
Product92_9057036-FI	PB-spread	Finland	4.20	3.20	0.05	0.65	0.03	0.27
Product93_8680037-FI	PB-spread	Finland	3.52	3.00	0.10	0.14	0.03	0.25
Product94_8854468-FI	PB-spread	Finland	2.64	2.13	0.10	0.13	0.03	0.25
Product95_8588111-FI	PB-spread	Finland	1.85	1.36	0.10	0.12	0.03	0.25
Product96_8587428-FI	PB-spread	Finland	2.43	1.87	0.09	0.19	0.03	0.25
Product97_8623213-FI	PB-spread	Finland	1.59	1.09	0.10	0.12	0.03	0.25
Product98_8592204-FI	PB-spread	Finland	1.93	1.43	0.10	0.12	0.03	0.25
Product99_9171823-FR	PB-spread	France	4.04	2.87	0.04	0.80	0.01	0.31
Product100_8716407-FR	PB-spread	France	4.02	3.15	0.05	0.50	0.01	0.31
Product101_8716422-FR	PB-spread	France	3.30	2.44	0.05	0.49	0.01	0.31
Product102_8939673-FR	PB-spread	France	3.84	2.91	0.09	0.52	0.01	0.31
Product103_8716972-FR	PB-spread	France	2.62	1.71	0.11	0.49	0.01	0.31
Product104_9114666-FR	PB-spread	France	4.60	3.71	0.05	0.51	0.01	0.31
Product105_8941210-FR	PB-spread	France	3.68	2.87	0.05	0.45	0.01	0.31
Product106_8919936-GR	PB-spread	Greece	5.90	4.29	0.05	1.15	0.11	0.31
Product107_8800658-GR	PB-spread	Greece	3.78	2.41	0.04	0.97	0.11	0.26
Product108_1031196-GR	PB-spread	Greece	5.93	4.70	0.04	0.99	0.11	0.10
Product109_8630227-GR	PB-spread	Greece	2.87	2.37	0.03	0.09	0.11	0.26
Product110_8751710-GR	PB-spread	Greece	2.13	1.64	0.03	0.09	0.11	0.26
Product111_8564454-GR	PB-spread	Greece	4.72	4.37	0.03	0.10	0.11	0.10
Product112_8715874-GR	PB-spread	Greece	3.13	2.63	0.03	0.10	0.11	0.26
Product113_9018021-HU	PB-spread	Hungary	3.75	3.01	0.04	0.38	0.06	0.27
Product114_8675323-HU	PB-spread	Hungary	1.08	0.75	0.03	0.04	0.06	0.19
Product115_8756278-HU	PB-spread	Hungary	1.86	1.25	0.04	0.31	0.06	0.19
Product116_8867358-HU	PB-spread	Hungary	4.20	3.50	0.04	0.33	0.06	0.27
Product117_9190688-HU	PB-spread	Hungary	2.72	2.04	0.04	0.32	0.06	0.27

Product118_8867833-HU	PB-spread	Hungary	4.04	3.50	0.04	0.33	0.06	0.10
Product119_9233728-HU	PB-spread	Hungary	2.51	1.82	0.04	0.32	0.06	0.27
Product120_8856605-HU	PB-spread	Hungary	3.58	3.15	0.03	0.07	0.06	0.27
Product121_9236827-HU	PB-spread	Hungary	2.87	1.90	0.05	0.69	0.06	0.16
Product122_8919936-HU	PB-spread	Hungary	4.95	4.18	0.04	0.34	0.06	0.33
Product123_9226791-HU	PB-spread	Hungary	4.25	3.51	0.04	0.37	0.06	0.27
Product124_8914273-IE	PB-spread	Ireland	4.92	4.22	0.05	0.31	0.07	0.27
Product125_8518006-IE	PB-spread	Ireland	2.47	1.88	0.15	0.11	0.07	0.27
Product126_8518082-IE	PB-spread	Ireland	3.68	3.12	0.15	0.12	0.07	0.22
Product127_8588122-IE	PB-spread	Ireland	2.56	1.95	0.05	0.27	0.07	0.22
Product128_9019796-IE	PB-spread	Ireland	5.88	5.16	0.05	0.32	0.07	0.28
Product129_8740001-IE	PB-spread	Ireland	1.88	1.37	0.14	0.08	0.07	0.22
Product130_8954218-IE	PB-spread	Ireland	2.68	2.14	0.14	0.11	0.07	0.22
Product131_8939673-IE	PB-spread	Ireland	3.28	2.67	0.15	0.12	0.07	0.27
Product132_8517980-IE	PB-spread	Ireland	2.19	1.62	0.15	0.09	0.07	0.27
Product133_8518007-IE	PB-spread	Ireland	2.08	1.50	0.15	0.09	0.07	0.27
Product134_9171823-NL	PB-spread	Netherlands	3.41	2.82	0.04	0.12	0.06	0.37
Product135_8820465-NL	PB-spread	Netherlands	4.49	3.89	0.05	0.19	0.06	0.30
Product136_8740005-NL	PB-spread	Netherlands	1.68	1.22	0.04	0.05	0.06	0.30
Product137_9138809-NL	PB-spread	Netherlands	4.91	4.25	0.05	0.17	0.06	0.37
Product138_8594809-NL	PB-spread	Netherlands	2.33	1.78	0.05	0.13	0.06	0.30
Product139_8740004-NL	PB-spread	Netherlands	2.78	2.29	0.05	0.09	0.06	0.30
Product140_8629141-NL	PB-spread	Netherlands	2.47	1.93	0.05	0.13	0.06	0.30
Product141_8629137-NL	PB-spread	Netherlands	2.51	1.97	0.05	0.13	0.06	0.30
Product142_8637225-NL	PB-spread	Netherlands	2.41	1.87	0.05	0.13	0.06	0.30
Product143_8751272-NL	PB-spread	Netherlands	3.85	3.51	0.05	0.13	0.06	0.10
Product144_8919936-NL	PB-spread	Netherlands	4.86	4.27	0.05	0.11	0.06	0.37
Product145_9106654-PL	PB-spread	Poland	2.14	1.64	0.04	0.07	0.12	0.26
Product146_8867358-PL	PB-spread	Poland	3.97	3.38	0.05	0.15	0.12	0.26
Product147_8867833-PL	PB-spread	Poland	3.73	3.38	0.04	0.09	0.12	0.10
Product148_8783427-PL	PB-spread	Poland	3.40	3.05	0.04	0.09	0.12	0.10
Product149_9190688-PL	PB-spread	Poland	2.48	1.98	0.04	0.08	0.12	0.26
Product150_9233727-PL	PB-spread	Poland	3.18	2.64	0.04	0.11	0.12	0.26
Product151_9233728-PL	PB-spread	Poland	2.31	1.80	0.04	0.09	0.12	0.26
Product152_8919936-PL	PB-spread	Poland	4.72	4.14	0.04	0.10	0.12	0.32
Product153_8500332-PT	PB-spread	Portugal	5.02	4.50	0.11	0.07	0.06	0.27
Product154_8473731-PT	PB-spread	Portugal	4.19	3.68	0.11	0.07	0.06	0.27
Product155_8626608-PT	PB-spread	Portugal	3.32	1.84	0.05	1.09	0.06	0.27
Product156_9091992-PT	PB-spread	Portugal	2.96	2.45	0.11	0.06	0.06	0.27
Product157_8710390-PT	PB-spread	Portugal	5.15	4.63	0.11	0.07	0.06	0.27

Product158_8761848-PT	PB-spread	Portugal	4.45	4.11	0.11	0.06	0.06	0.10
Product159_8867358-RO	PB-spread	Romania	4.25	3.16	0.04	0.71	0.08	0.26
Product160_8724230-RO	PB-spread	Romania	2.24	1.24	0.04	0.69	0.08	0.19
Product161_8294470-RO	PB-spread	Romania	1.06	0.70	0.03	0.06	0.08	0.19
Product162_9233727-RO	PB-spread	Romania	3.73	2.62	0.04	0.73	0.08	0.26
Product163_9233728-RO	PB-spread	Romania	2.85	1.77	0.04	0.70	0.08	0.26
Product164_9190688-RO	PB-spread	Romania	2.96	1.89	0.04	0.70	0.08	0.26
Product165_8856605-RO	PB-spread	Romania	3.31	2.85	0.03	0.10	0.08	0.26
Product166_9226791-RO	PB-spread	Romania	4.58	3.46	0.04	0.75	0.08	0.26
Product167_8898753-SE	PB-spread	Sweden	3.00	2.52	0.10	0.09	0.01	0.28
Product168_9168816-SE	PB-spread	Sweden	1.70	1.23	0.10	0.08	0.01	0.28
Product169_9138901-SE	PB-spread	Sweden	5.01	4.03	0.05	0.63	0.01	0.28
Product170_8933408-SE	PB-spread	Sweden	4.03	3.08	0.05	0.58	0.01	0.31
Product171_9171823-SE	PB-spread	Sweden	3.68	2.66	0.04	0.63	0.01	0.35
Product172_8919936-SE	PB-spread	Sweden	4.69	3.95	0.08	0.30	0.01	0.35
Product173_8854468-SE	PB-spread	Sweden	2.57	2.09	0.10	0.09	0.01	0.28
Product174_8680037-SE	PB-spread	Sweden	3.45	2.96	0.10	0.10	0.01	0.28
Product175_9213754-SE	PB-spread	Sweden	2.13	1.65	0.10	0.09	0.01	0.28
Product176_8623213-SE	PB-spread	Sweden	1.55	1.08	0.10	0.08	0.01	0.28
Product177_8592204-SE	PB-spread	Sweden	1.88	1.41	0.10	0.08	0.01	0.28
Product178_8933389-SE	PB-spread	Sweden	2.81	1.87	0.05	0.58	0.01	0.31
Product179_9155140-SE	PB-spread	Sweden	4.92	4.18	0.04	0.59	0.01	0.11
Product180_9057036-SE	PB-spread	Sweden	4.18	3.20	0.05	0.61	0.01	0.31
Product181_9049971-SE	PB-spread	Sweden	3.21	2.90	0.10	0.10	0.01	0.11
Product182_9018021-SK	PB-spread	Slovakia	3.57	2.85	0.04	0.34	0.06	0.27
Product183_8867358-SK	PB-spread	Slovakia	3.60	3.06	0.14	0.07	0.06	0.27
Product184_8867833-SK	PB-spread	Slovakia	3.50	3.00	0.04	0.29	0.06	0.10
Product185_8783427-SK	PB-spread	Slovakia	3.20	2.71	0.04	0.29	0.06	0.10
Product186_8724230-SK	PB-spread	Slovakia	1.78	1.21	0.04	0.27	0.06	0.20
Product187_8675323-SK	PB-spread	Slovakia	1.17	0.61	0.04	0.26	0.06	0.20
Product188_8735122-SK	PB-spread	Slovakia	1.70	1.13	0.04	0.27	0.06	0.20
Product189_9233728-SK	PB-spread	Slovakia	2.41	1.75	0.04	0.29	0.06	0.27
Product190_8695998-SK	PB-spread	Slovakia	2.14	1.48	0.04	0.29	0.06	0.27
Product191_9233727-SK	PB-spread	Slovakia	3.28	2.60	0.04	0.31	0.06	0.27
Product192_8919936-SK	PB-spread	Slovakia	4.73	4.00	0.04	0.30	0.06	0.33
Product193_8518008-UK	PB-spread	United Kingdom	1.70	1.12	0.15	0.08	0.07	0.27
Product194_8914273-UK	PB-spread	United Kingdom	4.85	4.14	0.05	0.31	0.07	0.27
Product195_8518006-UK	PB-spread	United Kingdom	2.44	1.84	0.15	0.11	0.07	0.27
Product196_8518082-UK	PB-spread	United Kingdom	3.64	3.08	0.15	0.12	0.07	0.22

Product197_8588122-UK	PB-spread	United Kingdom	2.48	1.86	0.05	0.27	0.07	0.22
Product198_9019796-UK	PB-spread	United Kingdom	5.81	5.09	0.05	0.32	0.07	0.28
Product199_8740001-UK	PB-spread	United Kingdom	1.87	1.35	0.14	0.08	0.07	0.22
Product200_8954218-UK	PB-spread	United Kingdom	2.65	2.11	0.14	0.11	0.07	0.22
Product201_8939673-UK	PB-spread	United Kingdom	3.25	2.64	0.15	0.12	0.07	0.27
Product202_8517980-UK	PB-spread	United Kingdom	2.17	1.59	0.15	0.09	0.07	0.27
Product203_8518007-UK	PB-spread	United Kingdom	2.07	1.48	0.15	0.09	0.07	0.27
Product204_84146485-US	PB-spread	United States	2.79	1.72	0.08	0.70	0.08	0.21
Product205_84146516-US	PB-spread	United States	2.77	1.71	0.08	0.69	0.08	0.21
Product206_84146529-US	PB-spread	United States	2.40	1.35	0.08	0.69	0.08	0.21
Product207_84147017-US	PB-spread	United States	2.98	1.92	0.08	0.69	0.08	0.21
Product208_84117084-US	PB-spread	United States	4.59	3.64	0.08	0.70	0.08	0.09
Product209_84137908-US	PB-spread	United States	3.22	2.16	0.08	0.69	0.08	0.21
Product210_84138021-US	PB-spread	United States	2.47	1.42	0.08	0.69	0.08	0.21
Product211_84139794-US	PB-spread	United States	3.66	2.72	0.08	0.69	0.08	0.09
Product212_84107197-US	PB-spread	United States	4.73	3.64	0.08	0.70	0.08	0.23
Product213_7803432-AT	PB-cream	Austria	2.43	1.36	0.12	0.47	0.02	0.46
Product214_7803432-CH	PB-cream	Switzerland	2.29	1.36	0.12	0.34	0.01	0.48
Product215_8225266-DE	PB-cream	Germany	1.50	0.81	0.12	0.09	0.04	0.44
Product216_7803432-DE	PB-cream	Germany	2.06	1.37	0.12	0.10	0.04	0.44
Product217_9016504-DE	PB-cream	Germany	2.73	2.03	0.12	0.10	0.04	0.44
Product218_2019002-FI	PB-cream	Finland	1.11	0.81	0.10	0.11	0.02	0.07
Product219_8292148-FI	PB-cream	Finland	0.85	0.56	0.10	0.10	0.02	0.07
Product220_8631323-FI	PB-cream	Finland	2.23	1.92	0.10	0.11	0.02	0.07
Product221_9144844-FI	PB-cream	Finland	0.96	0.66	0.10	0.11	0.02	0.07
Product222_1000949-FI	PB-cream	Finland	2.76	2.42	0.10	0.16	0.02	0.07
Product223_2019204-FI	PB-cream	Finland	1.75	1.41	0.10	0.15	0.02	0.07
Product224_2019002-SE	PB-cream	Sweden	1.07	0.81	0.10	0.08	0.00	0.07
Product225_8292148-SE	PB-cream	Sweden	0.81	0.57	0.10	0.07	0.00	0.07
Product226_8631323-SE	PB-cream	Sweden	2.19	1.94	0.10	0.08	0.00	0.07
Product227_1000949-SE	PB-cream	Sweden	2.80	2.51	0.10	0.12	0.00	0.07
Product228_2019001-SE	PB-cream	Sweden	2.42	2.13	0.10	0.11	0.00	0.07
Product229_Dairy spread_75% fat-DK	Dairy spread	Denmark	9.36	8.24	0.75	0.10	0.04	0.22
Product230_Dairy spread_40% fat-FI	Dairy spread	Finland	5.68	4.73	0.60	0.10	0.03	0.22
Product231_Dairy spread_60% fat-FI	Dairy spread	Finland	7.58	6.55	0.67	0.10	0.03	0.22
Product232_Dairy spread_75% fat-FI	Dairy spread	Finland	8.96	7.91	0.70	0.10	0.03	0.22
Product233_Dairy spread_40% fat-SE	Dairy spread	Sweden	6.02	5.16	0.50	0.10	0.01	0.25
Product234_Dairy spread_60% fat-SE	Dairy spread	Sweden	8.05	7.15	0.54	0.10	0.01	0.25

Product235_Dairy spread_75% fat-SE	Dairy spread	Sweden	9.53	8.63	0.54	0.10	0.01	0.25
Product236_Cream_30 % fat-AT	Dairy cream	Austria	5.62	4.73	0.35	0.10	0.02	0.42
Product237_Cream_30 % fat-CH	Dairy cream	Switzerland	5.17	4.35	0.27	0.10	0.01	0.44
Product238_Cream_30 % fat-DE	Dairy cream	Germany	5.25	4.29	0.42	0.10	0.04	0.41
Product239_Cream_15 % fat-FI	Dairy cream	Finland	1.88	1.57	0.15	0.10	0.02	0.04
Product240_Cream_27 % fat-FI	Dairy cream	Finland	3.27	2.84	0.28	0.10	0.02	0.04
Product241_Cream_40 % fat-FI	Dairy cream	Finland	4.83	4.26	0.42	0.10	0.02	0.04
Product242_Cream_15 % fat-SE	Dairy cream	Sweden	1.96	1.72	0.11	0.10	0.00	0.03
Product243_Cream_27 % fat-SE	Dairy cream	Sweden	3.43	3.10	0.20	0.10	0.00	0.03
Product244_Cream_40 % fat-SE	Dairy cream	Sweden	5.09	4.65	0.30	0.10	0.00	0.03
Product245_Vanilla whip-001_FI	Dairy cream	Finland	3.18	2.68	0.35	0.10	0.02	0.04
Product246_Vanilla whip-002_FI	Dairy cream	Finland	3.47	2.98	0.34	0.10	0.02	0.04
Product247_Vanilla whip_003-SE	Dairy cream	Sweden	2.20	1.85	0.22	0.10	0.00	0.03
Product248_Butter-AT	Dairy Butter	Austria	13.64	12.81	0.63	0.10	0.04	0.05
Product249_Butter-BE	Dairy Butter	Belgium	12.74	12.00	0.55	0.10	0.03	0.05
Product250_Butter-CA	Dairy Butter	Canada	11.06	10.37	0.53	0.11	0.03	0.02
Product251_Butter-CH	Dairy Butter	Switzerland	12.38	11.78	0.43	0.10	0.01	0.05
Product252_Butter-CZ	Dairy Butter	Czech Republic	11.96	10.78	0.93	0.10	0.09	0.06
Product253_Butter-DE	Dairy Butter	Germany	12.68	11.64	0.82	0.10	0.07	0.05
Product254_Butter-DK	Dairy Butter	Denmark	9.87	9.08	0.60	0.10	0.04	0.05
Product255_Butter-ES	Dairy Butter	Spain	14.47	13.58	0.67	0.10	0.05	0.06
Product256_Butter-FI	Dairy Butter	Finland	9.45	8.71	0.55	0.10	0.03	0.06
Product257_Butter-FR	Dairy Butter	France	12.28	11.66	0.44	0.10	0.01	0.06
Product258_Butter-GR	Dairy Butter	Greece	14.20	12.91	1.02	0.10	0.11	0.06
Product259_Butter-HU	Dairy Butter	Hungary	10.43	9.48	0.72	0.10	0.06	0.06
Product260_Butter-IE	Dairy Butter	Ireland	11.77	10.77	0.77	0.10	0.07	0.06
Product261_Butter-NL	Dairy Butter	Netherlands	12.23	11.27	0.74	0.10	0.06	0.05
Product262_Butter-PL	Dairy Butter	Poland	13.12	11.77	1.07	0.10	0.12	0.06
Product263_Butter-PT	Dairy Butter	Portugal	14.47	13.53	0.72	0.10	0.06	0.06
Product264_Butter-RO	Dairy Butter	Romania	10.86	9.83	0.79	0.10	0.08	0.06
Product265_Butter-SE	Dairy Butter	Sweden	10.07	9.50	0.40	0.10	0.01	0.05
Product266_Butter-SK	Dairy Butter	Slovakia	12.06	11.10	0.73	0.10	0.06	0.06
Product267_Butter-UK	Dairy Butter	United Kingdom	12.37	11.35	0.78	0.10	0.07	0.06
Product268_Butter-US	Dairy Butter	United States	12.05	11.03	0.81	0.11	0.08	0.02
Weighted average results for each country and the 21 markets								
WeightedAve_PB-spread_AT	PB-spread	Austria	3.66	2.72	0.04	0.55	0.04	0.30
WeightedAve_PB-spread_BE	PB-spread	Belgium	3.61	2.93	0.05	0.30	0.03	0.30

WeightedAve_PB-spread_CA	PB-spread	Canada	2.23	1.72	0.06	0.19	0.03	0.23
WeightedAve_PB-spread_CH	PB-spread	Switzerland	2.93	2.13	0.05	0.43	0.01	0.31
WeightedAve_PB-spread_CZ	PB-spread	Czech Republic	3.23	2.54	0.05	0.32	0.09	0.22
WeightedAve_PB-spread_DE	PB-spread	Germany	2.96	2.32	0.05	0.25	0.07	0.27
WeightedAve_PB-spread_DK	PB-spread	Denmark	3.05	2.22	0.06	0.44	0.04	0.29
WeightedAve_PB-spread_ES	PB-spread	Spain	4.57	3.74	0.08	0.43	0.05	0.26
WeightedAve_PB-spread_FI	PB-spread	Finland	3.20	2.49	0.08	0.34	0.03	0.27
WeightedAve_PB-spread_FR	PB-spread	France	3.71	2.84	0.06	0.49	0.01	0.31
WeightedAve_PB-spread_GR	PB-spread	Greece	3.43	2.87	0.04	0.20	0.11	0.22
WeightedAve_PB-spread_HU	PB-spread	Hungary	2.96	2.34	0.04	0.29	0.06	0.23
WeightedAve_PB-spread_IE	PB-spread	Ireland	3.06	2.47	0.12	0.15	0.07	0.25
WeightedAve_PB-spread_NL	PB-spread	Netherlands	3.24	2.71	0.05	0.12	0.06	0.30
WeightedAve_PB-spread_PL	PB-spread	Poland	2.78	2.31	0.04	0.09	0.12	0.23
WeightedAve_PB-spread_PT	PB-spread	Portugal	4.20	3.67	0.11	0.14	0.06	0.22
WeightedAve_PB-spread_RO	PB-spread	Romania	2.37	1.61	0.03	0.44	0.08	0.22
WeightedAve_PB-spread_SE	PB-spread	Sweden	2.91	2.30	0.08	0.25	0.01	0.27
WeightedAve_PB-spread_SK	PB-spread	Slovakia	3.01	2.41	0.06	0.25	0.06	0.23
WeightedAve_PB-spread_UK	PB-spread	United Kingdom	2.99	2.39	0.12	0.16	0.07	0.26
WeightedAve_PB-spread_US	PB-spread	United States	3.09	2.07	0.08	0.69	0.08	0.17
WeightedAve_PB-spread_GLO	PB-spread	21 Markets	3.14	2.39	0.07	0.38	0.06	0.25
WeightedAve_Butter_GLO	Dairy Butter	21 Markets	12.10	11.17	0.73	0.11	0.06	0.05

Note: WeightedAve*: The country weighted average results for PB-spread are calculated based on market share of different product. The global weighted average results of 21 markets for PB-Spread and Dairy butter are calculated by multiplying the weighted country carbon footprint by the market share derived from the 2018 butter production data for respective countries.

Table S8-3 Carbon footprint (kg CO_2-eq) break-down by farm activities for 1 kg of raw milk input used by butter production

	Country	Code	Enteric emissions	Manure management	Feed: pasture	Pasture peat degradation	Feed: fodder	Fodder land use change	Other farm activities	Total
Raw milk	Austria	AT	0.60	0.27	0.02	0.00	0.28	0.20	0.09	1.45
Raw milk	Belgium	BE	0.54	0.21	0.03	0.00	0.28	0.21	0.08	1.36
Raw milk	Canada	CA	0.50	0.26	0.03	0.00	0.28	0.03	0.08	1.17
Raw milk	Switzerland	CH	0.58	0.21	0.06	0.01	0.25	0.15	0.07	1.33
Raw milk	Czech Republic	CZ	0.50	0.12	0.04	0.00	0.25	0.19	0.12	1.22
Raw milk	Germany	DE	0.52	0.21	0.03	0.03	0.25	0.17	0.10	1.31
Raw milk	Denmark	DK	0.39	0.17	0.01	0.00	0.22	0.14	0.09	1.03
Raw milk	Spain	ES	0.53	0.18	0.05	0.00	0.35	0.33	0.09	1.53
Raw milk	Finland	FI	0.43	0.10	0.03	0.06	0.21	0.08	0.08	0.98
Raw milk	France	FR	0.55	0.22	0.04	0.00	0.25	0.19	0.07	1.32
Raw milk	Greece	GR	0.53	0.23	0.02	0.00	0.32	0.24	0.12	1.46
Raw milk	Hungary	HU	0.52	0.11	0.06	0.00	0.18	0.10	0.10	1.07
Raw milk	Ireland	IE	0.52	0.08	0.13	0.14	0.14	0.11	0.10	1.22
Raw milk	Netherlands	NL	0.47	0.17	0.04	0.07	0.24	0.18	0.10	1.27
Raw milk	Poland	PL	0.61	0.06	0.10	0.20	0.16	0.12	0.08	1.33
Raw milk	Portugal	PT	0.55	0.14	0.08	0.00	0.34	0.32	0.10	1.53
Raw milk	Romania	RO	0.59	0.05	0.14	0.03	0.14	0.12	0.04	1.11
Raw milk	Sweden	SE	0.43	0.11	0.01	0.02	0.26	0.19	0.07	1.07
Raw milk	Slovakia	SK	0.54	0.09	0.09	0.01	0.25	0.20	0.08	1.25
Raw milk	UK	UK	0.52	0.18	0.05	0.01	0.31	0.18	0.03	1.28
Raw milk	USA	US	0.50	0.23	0.03	0.00	0.30	0.08	0.11	1.25
To produce 1 kg of butter, 8.85 kg of raw milk-equivalent (raw milk + cream) is needed as input										

Curriculum Vitae

Xun Liao

- Date of birth: October 17th, 1988
- Nationality: Chinese
- Language: Chinese (Native), English (Fluent)

Contact information

- Address: Promenade de Castellane 2, 1110 Morges
- Telephone: +41 079 685 7673
- Email: xun.liao@gmail.com

Areas of expertise

- Corporate climate strategy
- Product and corporate footprint
- Life cycle inventory database development/Agricultural food system / energy system modeling
- Spatialization, regionalization and trade modeling along the global value chain
- Programming in R, modeling with SimaPro/CSV/Excel

Education

Since 2014 École polytechnique fédérale de Lausanne (EPFL)
PhD Thesis: Regionalized Life Cycle Assessment of food and energy systems
Director and co-director: Francois Marechal, Manuele Margni

2008-2009 Johns Hopkins University (JHU) / Baltimore, MD USA
Master of Science in Environmental Management and Economics
2004-2008 Sichuan University (SCU) / Chengdu, Sichuan China
Bachelor of Science in Environmental Science (Focus: Life cycle assessment)

Work Experience

2014-present Senior consultant at Quantis /Lausanne, Switzerland

2010-2014 Consultant at Quantis /Boston, USA

Professional Academic services

Journal reviewer for International Journal of Life Cycle Assessment, Journal of Industrial Ecology, Journal of Cleaner Production, Applied Energy

Scientific publications and presentations

Publication included in this thesis

1. **Liao X***, et al. A general computational structure for process-based regionalized life cycle assessment (submitted manuscript)

2. **Liao X***, Gerichhausen MJW, Bengoa X, et al (2020) Large-scale regionalized LCA shows that plant-based fat spreads have a lower climate, land occupation and water scarcity impact than dairy butter. Int J Life Cycle Assess. https://doi.org/10.1007/s11367-019-01703-w

3. **Liao X***, et al. The carbon footprint of the Power-To-Gas (manuscript in preparation)

Additional publications

4. **Liao X*,** Fazio S, Sala S, et al. Key issues of connecting LCI and LCIA: overview and recommendations (Manuscript to be submitted)

5. Rivière G, Pion F, …, **Liao X**, et al (2021). Toward waste valorization by converting bioethanol production residues into nanoparticles and nanocomposite films https://www.sciencedirect.com/science/article/pii/S2214993721000245

6. Ma S., Lin M, Lin T-E, **Liao X**, et al (2021) Fuel cell-battery hybrid systems for mobility and off-grid applications: A review. Renewable and Sustainable Energy Reviews 135:110119. https://doi.org/10.1016/j.rser.2020.110119

7. Shi X, **Liao X*,** Li Y (2020) Quantification of freshwater consumption and scarcity footprints of hydrogen from water electrolysis: A methodology framework. Renewable Energy 154:786–796. https://doi.org/10.1016/j.renene.2020.03.026

8. Laurent A, Weidema BP, Bare J, **Liao X**, et al (2020) Methodological review and detailed guidance for the life cycle interpretation phase. Journal of Industrial Ecology n/a: https://doi.org/10.1111/jiec.13012

9. Mutel C, **Liao X**, Patouillard L, et al (2019) Overview and recommendations for regionalized life cycle impact assessment. Int J Life Cycle Assess 24:856–865. https://doi.org/10.1007/s11367-018-1539-4

10. Di Marcoberardino G, **Liao X**, Dauriat A, et al (2019) Life Cycle Assessment and Economic Analysis of an Innovative Biogas Membrane Reformer for Hydrogen Production. Processes 7:86. https://doi.org/10.3390/pr7020086

11. Frischknecht R, Bauer C, Bucher C, …, **Liao X**, et al (2018) LCA of key technologies for future electricity supply—68th LCA forum, Swiss Federal Institute of Technology, Zurich, 16 April, 2018. Int J Life Cycle Assess 23:1716–1721. https://doi.org/10.1007/s11367-018-1496-y Video URL: https://www.video.ethz.ch/events/lca/2018/spring/68th/4c39040c-83c8-467a-bd3d-bfe6f47e01a1.html

12. Verones F, Bare J, Bulle C, …, **Liao X**, et al (2017) LCIA framework and cross-cutting issues guidance within the UNEP-SETAC Life Cycle Initiative. Journal of Cleaner Production 161:957–967. https://doi.org/10.1016/j.jclepro.2017.05.206

Report Chapter

13. Verones F, **Liao X**, Maia de Souza D, Fantke P, Henderson A, Posthuma L, Laurent A (2019b) Cross-cutting Issues (Chapter 2). In: Global Guidance for Life Cycle Impact Assessment Indicators, Volume 2 – A basis for greener processes and products (Eds. Frischknecht R. & Jolliet O.). United Nations Environment Programme, UNEP, Paris. (Role: Leading the linking LCI and LCIA taskforce)

Selected Conference and forum presentations

14. **Liao X**; 2017; Incorporating FAO trade and production database to estimate supply chain location information for agricultural products; 67th Swiss LCA Discussion Forum, Zurich, Switzerland. URL: https://www.video.ethz.ch/events/lca/2017/autumn/67th/30cc1b93-26db-4630-b285-f7e9036ad8fe.html

15. **Liao X**, A. celebi, and F. Marechal; 2017; Sustainability Metric of Bio-based Products: Review and Case Studies; ACLCA conference, NH, USA.

16. **Liao X**, et al.; 2017; Computational Framework of Regionalized LCA In Agri-food Products and Its Application Into Comparing Vegetable Oils Products And Dairy Alternatives In 21 Countries; ACLCA conference, NH, USA.