Challenges with using subnational trade and environmental data in support of global agri-food supply chain sustainability

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Abstract

Meeting demand for agricultural commodities while tackling climate change, biodiversity loss and natural resource degradation is challenging. Powerful actors from governments and multi-national companies have set ambitious targets to reduce pressure on the natural environment. However, the complexity of global supply chains hinders connecting consuming actors to locations of production. Despite advances in tools and methods aiming to convert data into useful information about environmental concerns, the implementation of this knowledge into decision-making is lagging.

This thesis' contribution to knowledge is the development of fine-scale environmental impact assessment analyses of traded agricultural commodities informed by supply chain stakeholder requirements through semi-structured interviews and focus group discussions. Adopting the principles of Life Cycle Assessment, sub-national trade-flow mapping, and quantitative spatially-explicit analysis of environmental hotspots of agricultural production is conducted across multiple production countries. Four sustainability dimensions are included: land use change (LUC) emissions, biodiversity loss, water scarcity and soil productivity loss, and the sensitivity of results to methodological and data choices tested. Finally, the thesis explores how future land use change can be assessed by incorporating sub-national supply chain detail into predictive land use change models.

Results reveal stakeholders will benefit from incorporating multiple dimensions of sustainability in decision-making. Quantitative assessments show that the spatial variability of all studied sustainability dimensions is large and that geographic hotspots of LUC emissions do not overlap with other studied impact hotspots. Findings are sensitive to both methodological and data choices. Finally, incorporating sub-national supply chain mapping into predictive models resulted in projected land use change concentrated to fewer geographies.

Overall, the thesis concludes that assessing the impacts of agricultural trade requires multiple dimensions of sustainability to better inform supply chain decision making. Additionally, more research is needed on the comparison of data, indicators and methods to support robust environmental impact assessments going forward.

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Chapter 1 Introduction

Despite the urgent need to reduce detrimental environmental impacts of commodity production and the accelerated availability of data, tools and methods providing information about environmental concerns in supply chains, implementation of this knowledge into decision-making is lagging. Freely available sub-national supply chain mapping data have been extremely useful to reduce the opacity of complex global supply chain and to better allocate responsibility for impacts to actors. However, in this context, most research is focused on a few geographies and a few dimensions of sustainability with little research aiming to understand sustainability concerns across multiple impact categories and producing countries. To bridge this gap, the overall aim of this thesis is to explore how to build on sub-national supply chain mapping data to provide useful knowledge for distant actors to improve the environmental sustainability of agricultural commodities that are sourced through complex supply chains. To ensure relevance, this research is informed by the preferences of stakeholders and their information needs so that they are in a position to take evidence-based action. In this Chapter, I will introduce the study by first providing an overview of the background and context, followed by the state of the art in monitoring international supply chains, the knowledge gaps, the aims and contribution and finally the structural outline of the thesis.

1.1 Background

1.1.1 Pressures and impacts of agricultural food production

Meeting the demands of almost 8 billion people for food, feed and fuel while tackling major challenges such as climate change, biodiversity loss and land degradation is one of the biggest challenges of our century (Willemen et al., 2020; Steffen et al., 2015; Rockström et al., 2009). Agriculture is one of the biggest drivers of global environmental change, contributing 30 % of greenhouse gas emissions (Tubielle et al., 2014), 78 % of eutrophication (Poore and Nemecek, 2018) and is the largest contributor to natural habitat conversion (Ellis et al., 2021). Conversion of natural habitat is the largest driver of global biodiversity loss (IPBES, 2018), further accelerates greenhouse gas emissions (Baccini et al., 2012) and can alter local water and nutrient cycles (D'Odorico et al., 2018). Since the middle of the last century most cropland expansion has been at the expense of tropical forests in Latin America, Sub-Saharan Africa and Southeast Asia (Pendrill et al., 2022; Curtis et al., 2018; Ramankutty and Foley, 1999). However, agricultural production can also negatively affect existing cropland. The Intergovernmental Science-Policy Platform on

Biodiversity and Ecosystem Services (IPBES, 2018) warns that 75 % of agricultural land is already substantially degraded. For example, it is estimated that with current rates of soil erosion only 60 harvests may be possible until global topsoil is depleted as highlighted by the United Nation (UN)'s Food and Agriculture Organisation (FAO, 2015). This is threatening the long-term capacity of the agricultural system to provide food (Rockström et al., 2017). Overall, a change in current practice is urgently needed to transition to a global food system that is sustainable in the long-term (Willett et al., 2019; Rockström et al., 2017).

Besides agriculture's impact on the environment, agricultural production also heavily relies on natural resources increasing the risk to food supply in the long-term. Agriculture uses 70 % of worldwide withdrawn freshwater for irrigation (Foley et al., 2011), occupies around 40 % of ice- and desert-free land (Ellis, 2021) and consumes around 90 % of the non-renewable mineral phosphorus extracted per year (Cordell, Drangert and White, 2009). All of the five largest global risks to humanity in the next ten years identified by the World Economic Forum (2022) (i.e. failure to adapt to climate change, extreme weather events, biodiversity crises, natural resource scarcity and human environmental damage) will impact food production (De Amorim et al., 2018). Increasing competition for natural resources and fossil fuels explained most of the food price increase during the food crises between 2008 and 2011 (Mittal, 2009). These increases in food prices can lead to social and geo-political instability (Lambin et al., 2020). In future, competition from other sectors is also expected as the shift away from fossil fuels towards nuclear power, biofuel production and hydropower will require more land and water (D'Odorico et al., 2018). Therefore, research is needed to support policies for navigating this complexity and tackling the multiple crises of biodiversity, climate and soil degradation while meeting demand of a growing and prospering population (Rockström et al., 2020).

1.1.2 Evolution of public and private policies

Policymakers recognised five decades ago that to manage natural resources more sustainably collaborative action is crucial (UNEP, 1972). In 1992 at the Earth Summit in Rio de Janeiro in Brazil (UN, 1992) more than 150 countries signed the Convention on Biological Diversity (CBD, 2015). Then, given a need to provide an assessment on progress towards the Convention on Biological Diversity (CBD), the UN published the Millennium Ecosystem Assessment report (2005). The report revealed the continued alarming state of the majority of the world's ecosystems and aimed to drive actions to reverse this trend (Guerry et al., 2015). As a response, governments, businesses and nongovernmental organization created initiatives to tackle this challenge. However, it was realised that the focus on developing countries within the Millennium Development Goals left out the responsibility of developing countries. Therefore, the Sustainable Development Goals (SDG) were developed (UN, 2015) that demonstrate the interconnectedness of countries within a globalised economy. The SDGs bring together social, environmental and economic sustainability and place a high priority on sustainable consumption and food security (UN, 2015). In the implementation of the SDGs, interactions between different goals arise which can either be positive (co-benefits) or negative (trade-offs) (Nilsson, Griggs and Visbeck, 2016). Trade-offs can arise, for example, if consumption is encouraged to drive economic growth (goal 8) whilst reducing climate action (goal 13; Springmann et al., 2016). To make policy interventions effective, interactions between different SDGs need to be considered (Nilsson et al., 2018). A need for more integrated approaches is therefore recognised which is, for example, illustrated through the first joint workshop of the UN's Intergovernmental Panel on Climate Change (IPCC) with the Intergovernmental Panel on Biodiversity and Ecosystem Services last year (IPBES, 2021). However, the lack of a systematic approach to integrate biodiversity and climate is hindering solutions benefiting both climate and biodiversity (Pettorelli et al., 2021). Further benefits could be achieved via a systematic approach incorporating not only climate and biodiversity but also other dimensions of sustainability mentioned in the SDGs such as soil health and water scarcity (Allen, Metternicht and Wiedmann, 2018).

1.1.2.1 Policies to reduce deforestation

Governments and businesses have recognised the underpinning role that natural ecosystems have for climate, biodiversity and ecosystem services and therefore their importance to achieve the SDGs. One of the most prominent examples of efforts to protect ecosystems are efforts to reduce tropical deforestation from global supply chains. More than 180 companies, governments and civil society actors, through the New York Declaration on Forests (NYDF) in 2014 (UNFCCC, 2014), committed to halve the rate of deforestation by 2020 and aim to end deforestation by 2030 (Lambin et al., 2018), an objective that is far from being reached (Rod et al., 2021). During the UN Climate Change Conference of the Parties (COP) in Glasgow, the number of countries pledged to eliminate forest loss and degradation and protect ecosystems increased to 141 countries (Gasser, Ciais and Lewis, 2022). This now also included new signatories that had not signed the NYDF before, such as Argentina, Brazil, Paraguay, Indonesia and Malaysia (UN COP, 2021). To achieve these goals different private sector instruments exist. For instance examples are 1.) geographically- and commodity-focused agreements, such as the Soy Moratorium, a commitment by traders to exclude soybean suppliers which cleared forest in the Amazon after a certain cut-off date (Garrett et al., 2019), 2.) collective actions such as the Consumer Goods Forum representing more than 400 companies aiming to collectively reduce deforestation (Lambin et al., 2018) 3.) voluntary third-party certification standards (e.g., Roundtable on Responsible Soy (RTRS), Roundtable on Sustainable Palm Oil (RSPO) or 4.) individual company commitments (Virah-Sawmy et al., 2019; Garrett et al., 2019). However, the lack of implementation of zero-deforestation policies by the private sector has hindered progress to halt deforestation (Lambin et al., 2018). Therefore, some governments have begun discussions to introduce mandatory supply chain due diligence policies banning traders from importing 'forest-risk' commodities (i.e., soy, beef, palm oil, cocoa) produced on recently cleared land (Bager, Persson and dos Reis, 2021). However, meaningful progress on deforestation is still hindered by leakage to other biomes or commodities (Meyfroidt et al., 2018) and the lack of traceability and transparency to monitor compliance (Lambin et al., 2018).

1.1.3 The increasing importance of distant drivers that increase the complexity of sustainable production and consumption efforts

Changing consumption patterns enabled through the globalisation of trade are becoming increasingly important in both understanding and addressing drivers of environmental change (D'Odorico et al., 2017). Globalisation of trade lead in the last two decades to what D'Odorico et al. (2018) calls the "fourth food revolution" increasing the quantity and quality of available food (Kastner et al., 2021; Pendrill et al., 2019b). Trade has re-shaped global agricultural production and rising income levels have led to an increase in the demand for animal products such as meat, dairy and egg products. Resource-limited countries with high levels of animal production such as Europe, Japan and China increasingly rely on imported feed such as soy, wheat and corn (Wang et al., 2018). As animals are quite inefficient in the conversion of feed to food (Shepon et al., 2016), animal products have much higher greenhouse gas emissions, land use and water scarcity impacts compared to plant-based alternatives (Poore and Nemecek, 2018).

With globalisation of trade, production and consumption have become increasingly spatially disconnected (Erb et al., 2009). Due to this disconnection, changes in consumption patterns in one place can trigger changes in land use and management in other places (Lambin and Meyfroidt, 2011) leading to direct and indirect environmental and social impacts (Pendrill et al. 2019b; Liu et al., 2015; Liu et al., 2013). For example, in China animal-based calorie consumption increased by 45 % between 2000 and 2010 which required large imports of feed (mostly soy) making China the biggest global soybean importer (35 %; Zhao et al., 2021). As a result of this increased demand for soy, China contributed considerably to deforestation and ecosystem conversion in Brazil (Liu et al., 2013). Therefore, distant patterns in agri-food consumption and trade have become key determinants of global sustainability (Friis et al., 2016).

A lot of the impacts associated with animal products are due to feed cultivation which occupies around 40 % of global cropland (Mottet et al., 2017) and dominates with 67 % deforestation for agriculture, mostly due to soy, maize and pasture (Poore and Nemecek, 2018). As along the value chain most impacts occur on the farm (Poore and Nemecek, 2018), import of feed products can lead to the displacement of environmental impacts towards export-producing countries (Vermeulen, Campbell and Ingram, 2012). As deforestation and other ecosystem conversions are major drivers of global biodiversity loss and further accelerate climate change, addressing feedstock cultivation and trade is central to tackling biodiversity loss and climate change. This is likely to become even more important in future as the increase in animal products is expected to be the biggest contributor to the increase in global food demand of 35-65 % by 2050 (van Dijk et al., 2021; Alexander et al., 2015). This is projected to lead to an expected further 7 % increase of cropland globally without further agricultural intensification (Alexandratos and Bruinsma, 2012). However, the increase in food demand is geographically distributed unequally across the world (Alexandratos and Bruinsma, 2012). For example, China is expected to double its ruminant meat and dairy consumption from 2010 to 2050 making it then responsible for 46 % of global soybean trade (Zhao et al., 2021). Therefore, forward-looking land use and environmental impact models are needed that allow to understand the consequences of changes in consumption and trade on environmental impacts and future resilience of agriculture.

However, the complexity of supply chains and the multitude of actors present across scales, make it difficult to understand and predict consequences of changes in consumption and related policies and trade patterns (Liu, 2017). In land system science, the concept of 'telecoupling' has been suggested to study global sustainability and the interactions between socioeconomic and environmental systems across scales, long distances and disciplines (Friis et al., 2016; Liu et al., 2013). To further advance this field and guide global sustainability challenges, Hull and Liu (2018) argued that future research should: (1) enhance traceability of global products so that consumption can be linked to sub-national impacts of agricultural production, (2) identify trade-offs between local and global sustainability and (3) determine unknown spillover effects.

1.1.4 Private sector motivations and challenges to effect change

Multinational companies (MNCs) have grown in size and influence making them important actors in the transition towards global sustainable development outcomes (Brundtland, 1987). Companies have realised the detrimental effects climate change and other environmental changes can have on their businesses (Kareiva et al., 2015). In a survey among corporate leaders, 76 % considered addressing the world’s biggest challenges such as climate change to be crucial for the viability of their organization in the long-term (Ernst & Young, 2022). In addition to concerns about negative effects in the long term, motivations for companies to improve the sustainability include a) governments regulations (especially driven by USA and Europe), b) competitive advantage (through cost reduction and supply chain innovation), c) stakeholder expectations (especially in relation to reputation and requests to improve transparency) and d) supply disruptions due to local resource shortages or extreme climatic events (O'Rourke, 2014). As a response to these drivers many corporations have set ambitious sustainability commitments which were further accelerated through the UN Climate Change Conference in 2021. Such commitments include statements to eliminate forest loss from supply chains by 2030 (e.g., New York Declaration on Forests, 2014), participation in international agreements such as Aichi Biodiversity Targets (Folke et al., 2019; Lambin et al., 2018) and those linked to the Science-Based Targets Initiative for climate (SBTi, 2022). To date, more than 250 companies in the food and beverages sector have committed to set or already have set science-based targets for climate (SBTi, 2020). However, despite these pledges, progress on sustainability commitments is slow and changes in corporate practices are not sufficient to meaningfully tackle sustainability challenges (Ahlström, Williams and Vildåsen, 2020; NYDF Assessment Partners, 2019; Guerry et al., 2015).

One of the challenges for companies to affect change in their supply chains is that the origin of commodities is often unknown and methods to quantify actor-specific impacts (including land use change carbon emissions; SBTi, 2022) remain under development (Aké and Boiral, 2022). Advances in satellite Earth Observation offer the potential to monitor changes in the state of ecosystems such as forest loss in near real-time (Cord et al., 2017) allowing the verification of compliance with policy and private-industry regulations more cheaply than before where field inspections would have been necessary (Alix-Garcia and Gibbs, 2017). For example, in Brazil, the government encourages through the Rural Environment Registry (portuguese Cadastro Ambiental Rural; CAR) the collection of the boundaries of properties which could be combined with satellite data to monitor farmer’s compliance to Brazilian national policy (Alix-Garcia and Gibbs, 2017).

However, one of the challenges with the increasing availability of data through Earth Observation is to translate this data into information that can be incorporated into innovation and sourcing strategies of companies (O'Rourke, 2014). The companies for which it is hardest to identify the origin and associated impacts of their sourced commodities are multi-national manufacturers or retailers as they are often geographically the most distant from production systems but also have multiple tiers of suppliers between producing regions and their own company activities (Cammelli et al., 2022). In this thesis, I refer to these distant actors as ‘end-buyers’ of agricultural commodities. These end-buyers require decision-support tools that allow the monitoring and measurement of direct and indirect impacts of their innovation and sourcing decisions on global land use (Tonini and Liu, 2017; Bruckner et al., 2015).

1.2 State of the art in monitoring and assessment of international supply chain impacts

1.2.1 Identifying opportunities to improve the sustainability of agricultural systems

Mechanisms to meet humanity’s needs for food, such as via sustainable intensification of agriculture (SIA), without converting more ecosystems are highly debated. Rockström et al. (2017) argued that there needs to be a paradigm shift away from aiming to reduce agriculture’s negative impacts and towards agriculture becoming the world’s largest driver in the transformation towards global sustainability within ‘planetary boundaries’. These authors stress that SIA should focus beyond improving local productivity and efficiency in natural resource use, and on improving ecological functions crucial for the resilience of agriculture against increasing global environmental change (Rockström et al., 2017). Suggested practical solutions include, for example, planning landscapes as a mosaic of natural, semi-natural and agricultural land to achieve multiple ecological functions and changing farming practices to reduce soil erosion (Rockström et al., 2017). However, there is a gap in terms of the data, indicators and metrics (especially for biodiversity and soils at landscape scales) to monitor where environmental concerns that could be addressed with such interventions are most prevalent, or whether these suggested solutions are actually achieving their anticipated outcomes (Cassman and Grassini, 2020). Considering that different world regions are different in their environmental and socio-economic context and therefore effective solutions for SIA will likely depend on local characteristics (Weltin et al., 2018), data and indicators are needed to identify in which contexts specific interventions are required to achieve the desired outcomes.

1.2.2 Strategies for more sustainable sourcing of agri-commodities

Considering that trade plays a major role for many global sustainability challenges and that 80 % of traded goods are sourced by multi-national companies (UNCTAD, 2013), supply chains are key to the achievement of Sustainable Development Goals. Companies' sustainable sourcing practices can be defined as "voluntary practices companies pursue to improve the social and/or environmental management of their suppliers' activities" (Thorlakson, Zegher and Lambin, 2018, p.2072). The focus in this thesis will be on research that supports the sustainable sourcing of agricultural commodities, and soybeans are selected as representative and globally important example as the export commodity with the biggest impact on global deforestation and potential species loss compared to other commodities (Kastner et al., 2021).

Soybeans are the world's most internationally traded agricultural commodity due to their use in animal-feed (COMTRADE, 2020) but also other uses such as cooking oil and biofuel production (Castanheira and Freire, 2013). From 2000 to 2020, the international trade in soybeans quadrupled (FAOSTAT, 2021), driven by the increasing demand for animal products in China and other developing markets. This increase in soybean export largely came from Brazil (700 %), Paraguay (200 %), USA (130 %) and Argentina (100 %) which are all among the five largest global soybean producers (FAOSTAT, 2021). This acceleration in production lead to soybeans becoming one of the key commodities driving most deforestation and natural vegetation loss globally (Pendrill et al. 2019b). As a response to the growing concern by consumers, governments, traders and multi-national companies (Nepstad et al., 2014); several supply chain policies were established aiming to reduce detrimental environmental impacts of soybean expansion.

1.2.2.1 Landscape/jurisdictional approaches

Out of a realisation that limited market share limits the effectiveness of eco-certification to tackle deforestation and unsustainable resource use in the tropics (Garrett et al., 2019), landscape approaches have been suggested as a more effective strategy for the transition towards sustainable production (Von Essen and Lambin, 2021). Considering that agriculture relies on ecosystem services generated outside of the strict boundaries of a farm such as freshwater provisioning for irrigation, soil erosion control or pollination, the landscape scale is considered as more appropriate than farm scale management (TEEB, 2018a). Commodity-centric landscape governance has emerged where multiple stakeholders aim to address sustainability challenges related to commodity production within a specific geographic area (Bastos Lima and Persson, 2020). Examples of this geographic area can be for soy at the scale of either an ecoregion or a biome such as the Amazon Soy Moratorium, or the activities of the Cerrado Working Group. Examples for palm oil are at a sub-national jurisdictional level the 100 % Roundtable Sustainable Palm Oil (RSPO) approach in Sabah in Malaysia (Zu Ermgassen et al., 2022). Focusing efforts on an entire jurisdiction or landscape provides the opportunity to bring all relevant stakeholders together (e.g., smallholders, local government, private sector) thereby addressing drivers of unsustainable land use outside of the farm such as speculative land conversion (Brandão et al., 2020). However, there are challenges in the implementation and operationalisation of landscape approaches. Firstly, existing power imbalances between stakeholders can result in distant powerful actors (e.g., international NGOs, western consumers) dominating which sustainability concerns are being focused on such as tropical deforestation rather than concerns of local producers such as loss of agrobiodiversity, access to water resources or pesticide pollution (Bastos Lima and Persson, 2020). Secondly, there is a lack of monitoring of the outcomes (Von Essen and Lambin, 2021). Therefore, research is needed on how to monitor outcomes of landscape approaches more holistically which include, besides those of distant powerful actors, also the concerns of local actors.

In a globally-interconnected trade market, policies restricting access to one region can cause indirect effects such as the displacement of agricultural expansion to other regions. Efforts to reduce detrimental land use change which focus on few locations can displace ecosystem conversion to other regions or commodities (leakage) as the overall commodity demand remains constant (Lambin et al., 2018; Garrett, Rueda and Lambin, 2013). For example, while the Soy Moratorium decreased deforestation in the Brazilian Amazonian biome, soy expansion increased in the neighbouring savannah Cerrado (Gibbs et al., 2015). Additionally, local leakage can take place when soy-farmers deforest for the cultivation of crops not part of the Soy Moratorium efforts such as corn or cattle ranching (Gibbs et al., 2015). Compliance to country-specific supply chain initiatives or producing government's anti-deforestation regulations could also lead to leakage in other countries (Le Polain de Waroux et al., 2019). Arima et al. (2014) also argue that any environmental achievements in reducing deforestation in the Amazon could be outweighed if it leads to agricultural expansion in other ecosystems such as the dry forest biome Chaco in Argentina and Paraguay or the Atlantic rainforest in south-eastern Brazil. However, understanding these indirect effects of policies in other locations affected by different regulations and socio-economic characteristics is challenging (Levine-Schnur, 2016). If efforts prioritise few geographies or commodities, leakage to other commodities or geographies is likely (Meyfroidt et al., 2018). In this thesis, while analyses of the dynamics of land use change leakage and evaluating multiple commodities is out of scope of the quantitative research, I adopt a consistent approach to assess impacts across multiple producing countries and/or regions and biomes to account for leakage to a certain extent. Identifying geographic hotspots of impacts across producing regions and connecting them to distant actors, allows identification of the responsibility of actors for impacts but also the targeting of interventions to those regions where they are most needed (Green et al., 2019). Retaining a broader geographic scope in the analyses avoids missing less-studied geographic hotspots such as Paraguay or the dry forest Chaco in Argentina (Gardner et al., 2019).

1.2.2.2 Transparency as a tool to improve sustainability in global complex supply chains

Globalisation of trade has created complex supply chains where regions of production and consumption are often spatially disconnected (Meyfroidt et al., 2013). Therefore, identifying the origin of a purchased commodity and to which extent it caused local or global impacts during its agricultural production is challenging (Eakin, Rueda and Mahanti, 2017). However, knowing where the impacts are is crucially important to prioritise efforts to identify impact hotspots and target interventions. This complexity hinders ascribing responsibility among different actors such as producers, producing governments, traders, manufacturers and retailers, and therefore ultimately the effectiveness of supply chain governance (Gardner et al., 2019). As there is a huge spatial variability in sourcing regions' impacts (e.g., land use change, biodiversity damage, carbon emissions), mapping sub-national trade flows is crucial for a robust assessment of commodities' footprint (Green et al., 2019; Zu Ermgassen et al., 2020a).

Recently, novel technologies have allowed improvements in the traceability and transparency of global complex supply chains. This includes the – originally titled - Transparency for Sustainable Economies Initiative (now known as Trase) of the Stockholm Environment Institute and Global Canopy (Folke et al., 2019). Trase is a platform (www.trase.earth) that provides actor-specific information on the links between trade and specific sourcing regions and therefore provides an important step towards reducing the complexity of assigning responsibility and roles for impacts within commodity supply chains (Virah-Sawmy et al., 2019). Trase's supply chains maps are created by using a range of different data sources such as trade data, tax information, shipping information and additional linear programming techniques to optimize transport distances between locations producing commodities and logistic infrastructure such as ports, silos and crushing facilities (Godar et al., 2016). This has allowed the connection of sub-national jurisdictions (e.g., municipalities in Brazil) that are producing commodities for export to be linked to the global markets buying those commodities depending on their sourcing volume from each jurisdiction. So far Trase's sub-national supply chain mapping focuses on key commodities causing detrimental impacts during production (i.e. soy, palm oil, beef, cocoa, coffee, corn, chicken, cotton, pork, shrimp and wood pulp) and their corresponding major production regions (i.e., Brazil, Argentina, Paraguay, Colombia, Ecuador, Indonesia, Cote d'Ivoire; see more details at https://trase.earth/).

However, whilst providing information specifically on land use change and deforestation has been a key focus of Trase, a lack of consistent environmental data used to estimate environmental impacts linked to those sub-national jurisdictions, hinders comparison of commodity footprints across producing countries. While initiatives like Trase raise awareness about sustainability concerns such as deforestation among western consumers and multi-national companies, they can only be considered a first step towards a food system transformation that respects ecological limits, according to Weber and Partzsch (2018). A challenge is that few leading companies currently implement traceable or transparent supply chains (Zu Ermgassen et al., 2020b). Despite progress in improving subnational supply chain mapping of commodities to better understand fine-scale impacts, these are limited to few geographies, commodities and indicators. However, Gardner et al. (2019) warns that as improved transparency makes some issues more visible than others, there is a risk that those more visible issues are perceived as more important than other issues. For example, in the case of transparency in global agricultural supply chains, the focus on a) certain indicators such as deforestation at the detriment of reducing conversion of other ecosystems or monitoring other environmental impacts, b) certain commodities such as palm rather than other commodities like coconut grown in similar geographies like palm or c) specific countries or biomes such as Brazil or the Amazon instead of other threatened biomes such as the Chaco or less well studied countries like Colombia (Gardner et al., 2019). In response, a more systematic approach is required to understand the impact of trade on multiple dimensions of sustainability (Kastner et al., 2021), quantified consistently across a range of producing countries to identify trade-offs and synergies. Using such an approach to inform decisions can reduce the likelihood of decisions leading to unintended consequences such as shifting the burden of production to other geographies or dimensions of sustainability.

The different concepts mentioned in this chapter such as planetary boundaries, systems thinking, transparency should be seen as complementary rather than one being superior to the other as each concept has its advantages in being able to change practices towards a sustainable society. For example ‘planetary boundaries’ has the advantage to highlight the finite nature of the earth (Whiteman et al., 2013), systems thinking stresses the complexity and the need to consider unintended consequences of interventions (Small et al., 2021) and transparency of supply chains allows to link the social (e.g., corporations, governments) to the ecological (e.g., forests) systems to raise awareness and identify responsible actors (Gardner et al., 2019).

1.2.3 Available footprinting and LCA methods

Resource and emission ‘footprints’ can be quantified at the scale of sectors or nations using Environmentally-Extended Multi-Regional Input-Output (EE-MRIO) models (Lenzen et al., 2022; Wiedmann and Lenzen, 2018). Alternatively, environmental impacts of products or processes along the entire value chain from agricultural production to use and disposal can be accounted for using a Life-cycle assessment (LCA) approach (Hellweg and Milà i Canals, 2014). In this context, different definitions of the term “footprints” exist (Matuštík and Kočí, 2021). Whereas the Environmental Footprint Accounting community (Vanham et al., 2019) largely understands “footprints” as human pressure indicators using a consumption perspective, the majority of the Life Cycle Assessment (LCA) community (Ridoutt et al., 2015) understands “footprints” as impacts therefore considering footprints as LCAs reduced to a single impact class (Matuštík and Kočí, 2021). In this thesis, I will use the term as referred to in the LCA community. In LCA, negative impacts are usually assessed for multiple impact categories together, such as climate change, water scarcity and biodiversity damage (Verones et al. 2017). In industry, LCA is an important tool to understand a product’s sustainability, supplier’s environmental performance or to report on a companies’ carbon footprint (Stewart et al., 2018). Widespread use by practitioners has also been facilitated through intense efforts to harmonise and develop internationally-agreed standards (Jolliet et al., 2018; Ridoutt et al., 2015; JRC-IES, 2010; ISO 14044, 2006) and to provide accessible databases such as the world food LCA database (Peano et al., 2012) offering detailed greenhouse gas emissions data for many food products cultivated in corresponding key producing countries. Recently, the use of LCA has also been encouraged through several policy-making initiatives, for example in the European Union (EU) with the Product Environmental Footprint (PEF) and the Organization Environmental Footprint (OEF) developed for application in the private sector (EC, 2018, 2016). Increasingly both the public and the private sector require their suppliers to provide life-cycle based information about the environmental performance of their products (Jenssen and de Boer, 2019). Additionally, corporate initiatives such as the Greenhouse Gas Protocol (WRI/WBCSD, 2011) and the Science-Based Targets Initiative (SBTI) are recommending LCA methods for the forest, land and agricultural sector to measure and report on land-based greenhouse gas emissions in companies' supply chains (SBTI, 2023). Despite the widespread use of LCA in public and private decision-making (Jenssen and de Boer, 2019), LCA also has some limitations. While the multi-criteria approach and the perspective of the entire life cycle of products makes LCA studies a suitable method to guide decision-making this also increases the difficulty in communicating methods and results to non-experts as they can be very comprehensive in the environmental impact categories they include and thus require more technical detail and language to describe (Ridoutt et al., 2015). Another limitation of LCA studies is that comparability is often challenging as studies vary in assumptions, the 'system boundary' (which processes and impacts are included) or the functional unit (e.g., one 500-gramme tub of margarine) leading to the confusion of decision-makers (Vidergar et al., 2021).

While usually relatively wide-ranging in their coverage of impact categories, data availability can limit the level of detail in the underlying resource and emission inventories reducing the completeness of LCA studies, particularly for supply chains of agricultural commodities (Godar et al., 2016; Finkbeiner, 2014; Curran, Hellweg and Beck, 2014). A key challenge in this context is that farming practices are variable across production locations and commodities and their impacts are highly dependent on local context such as climatic factors, soil type and buffer zones around rivers (Poore and Nemecek, 2018). Therefore, assessing environmental impacts in supply chains of globally traded agricultural commodities needs to account for the heterogeneity in local characteristics and the surrounding landscape where commodities are grown (De Rosa, 2018; Notarnicola et al., 2017; Hellweg and Milà I Canals, 2014). However, methods accounting for spatial detail have only recently emerged in LCA, are often more time-intensive to apply for practitioners and there is still a lack of consensus on detailed methodological or data choices (Patouillard et al., 2019). These choices can result in highly variable results for some environmental impacts. For example, for soy-specific land use change emissions, tools developed for LCA practitioners, reported at Brazilian national scale: 15.6 t CO_2-eq./t soy-eq. in the 'LUC Impact tool' (Blonk Consultants, 2021); 6.9 t CO_2-eq./t soy-eq. in 'BRLUC' (Novaes et al. 2017); and 1.7 t CO_2-eq./t soy-eq. in 'GeoFootprint' (Reinhard et al., 2021). In contrast, in scientific publications which accounted for the spatial variability in soybean LUC emissions in Brazil, estimates varied at municipality scale from 0.1-17.8 t CO_2-eq./t soy-eq in Castanheira and Freire (2013) and 0.1-29.47 t CO_2-eq./t soy-eq. in Escobar et al. (2020). Therefore, to further advance methods accounting for spatial detail in environmental impact assessment as well as in tools used by LCA practitioners, it is important that sources of uncertainty and variability are better understood.

As a complement to LCA-based approaches, an alternative method to study impacts of trade, are physical trade accounting methods estimating impacts from a 'top-down' perspective (Wiedmann and Lenzen, 2018; Henders, Persson and Kastner, 2015; Kastner, Erb and Haberl, 2014). However, similar to EE-MRIO models, physical trade accounting methods usually use national-level data, thereby ignoring variability in production practices and associated impacts (Pendrill et al. 2019b). Increasingly, hybrid approaches are being developed which combine physical and monetary trade flow accounting together with regionalised impact characterization factors from LCA to more broadly assess environmental footprints across sectors and countries (e.g., Croft, West and Green, 2018; Chaudhary and Kastner, 2016). The novel Trase data allows the quantification of environmental footprints with a high spatial resolution, such as illustrated for water scarcity and biodiversity footprints (e.g., Lathuillière et al., 2021). However, existing studies on sub-national environmental footprints of agricultural commodities have only assessed one or two impact categories (e.g., Escobar et al., 2020) limiting the ability to identify trade-offs across different dimensions of sustainability.

Research aiming to project future trade and consumption patterns ('what-if' scenarios) on global land use are also limited in their ability to link consuming countries to sub-national producing regions (Bhan et al., 2021). These models can support policy-makers wanting to understand the impacts of business as usual pathways, and the consequences of alternative actions and their efficacy in achieving sustainable development objectives (Leclère et al., 2020). For these research objectives, market dynamics matter to the outcomes of these scenarios and therefore economic general equilibrium or partial equilibrium models are typically appropriate tools for analysis (Millington et al., 2017). An advanced model of this kind that has been used commonly to support land use policies, is the so-called Global Biosphere Management Model (GLOBIOM), a global dynamic partial equilibrium model projecting land use into the future to 2050 (Havlik et al., 2013). However, to date, research incorporating sub-national supply chain mapping data into predictive land use change models is only in its infancy and uncertainty in projected environmental impacts remains (Soterroni et al., 2019).

1.3 Knowledge gaps

Building on the background and sustainability challenges (detailed in section 1.1) and the state of the art in monitoring and managing global supply chain impacts (detailed in section 1.2), the following section will describe the knowledge gaps which need to be addressed to support policy and practice. While advances have been made to generate novel data with unprecedented detail, a challenge is to convert these data into useful and actionable information for decision-makers in companies and governments (O'Rourke, 2014).

1.3.1 Regional detail

Despite the importance of the spatial resolution of production for robust environmental footprints of agricultural commodities, traditional LCA and conventional physical trade accounting methods (Section 1.2.3) typically do not consider the variability in impacts across sub-national growing regions. Existing studies analysing impacts at sub-national production scale focus on a single or few environmental concerns such as conversion of forest ecosystems (Zu Ermgassen et al. 2020a; Pendrill et al. 2019b), carbon emissions (Garofalo et al., 2022; Lam et al., 2021; Escobar et al., 2020) or biodiversity loss (Durán et al., 2020; Green et al., 2019; Chaudhary and Kastner, 2016) but do not make use of recent improvements in remote sensing providing global land cover maps (ESA CCI, 2017) or novel indicators of soil productivity loss (Sonderegger and Pfister, 2021). Assessing impacts on soils is crucial to understand whether land is managed sustainably to produce food in the long-term and should be included in LCA studies (Notarnicola et al. 2017). One challenge to improve the spatial detail of footprints is that data are either not available (such as farming practices) or too time-consuming to gather or generate (such as commodity-specific land use change emissions; (Patouillard et al., 2019). Another challenge to mainstream spatially-resolved impact assessment is that some available data, such as those provided by Trase, are not consistent with LCA standards and thus cannot easily be incorporated into the most popular LCA software (Mutel et al., 2019). However, these software programmes are widely used by companies to calculate greenhouse gas emissions they report on (BSI PAS, 2012). Therefore, more research is needed that integrates spatial data and methods from a variety of research communities to provide consistent data that can be integrated into mainstream LCA software or databases used by practitioners.

1.3.2 Geographic coverage

Despite the importance of distant consumption and trade patterns for global sustainability (Friis et al., 2016) and the interconnectedness of markets (Meyfroidt et al. 2018), to-date comprehensive (multi-country) and consistent assessments of sub-national environmental footprints linked to commodity consumption are scarce. Existing studies on sub-national environmental footprints of commodity consumption have analysed one or two countries in isolation such as Brazil (e.g., Lathuillière et al., 2021; Flach et al., 2016; Escobar et al., 2020) or Indonesia (e.g., Lam et al., 2021), but – beyond tropical deforestation – there are a lack of studies providing consistent analyses of multiple sub-national producing regions. A challenge here again is availability of data which often limits application of fine-scale data and methods to data-rich countries such as Brazil (Diniz et al., 2013). Nevertheless, to support international trade agreements and multi-national companies with global supply chains, a supranational scale is required for analyses (Bhan et al., 2021). Such analyses would help to prioritise actions by highlighting regions requiring attention and by recognising potential of burden shifting (Bager et al. 2021) which would ultimately allow improvements in the sustainability criteria of trade agreements (Kehoe et al., 2019) and of corporate supply chain policies. A better understanding across landscapes of the links between trade and global environmental concerns like deforestation, biodiversity loss and soil degradation would help to guide actions to achieve global sustainability goals such as eliminating deforestation from supply chains (Lambin et al., 2018), and achieving Aichi biodiversity targets and the Sustainable Development Goals (Kastner et al., 2021). A more holistic and multi-indicator analyses would also help to identify trade-offs and synergies which is encouraged through the framework of the SDGs (Nilsson et al. 2016).

1.3.3 Lack of intercomparison, high uncertainty and variability

While a lot of research has focused on understanding variability and uncertainty in environmental impacts of agricultural products due to farming practices and spatial variability in local characteristics, less is known about how methodological and data choices affect estimates of environmental impacts. In this context, it is important to differentiate between uncertainty and variability: whereas uncertainty can be reduced through further research, variability is due to actual differences between producing regions such as soil properties or climatic conditions (and therefore cannot be reduced with more research; Steinmann et al., 2014). One of the most highly debated aspects related to estimating environmental impacts of agricultural and food products are LUC emissions (Sevigné-Itoiz et al., 2021). LUC emissions can have a substantial contribution to the overall life-cycle emissions of a product (such as 86 % of the total in the case of Brazilian soybean oil; Liao et al. 2020). Despite the importance of this issue, and the wealth of studies about LUC emissions, there is still a lack of consensus about methodologies in LCA (De Rosa, Pizzol and Schmidt, 2018). As a result of this lack of consensus, results can be highly variable between studies and up to now it is not clear to what extent these differences are due to methodological choices, different data sources varying in spatial resolution (Donke et al., 2020) or underlying assumptions

(Garofalo et al., 2022). While the range in LUC emissions is comparatively well understood, less is known about the range of other environmental impacts of agricultural commodities or which factors affect this range. Therefore, understanding how methodological choices, different available datasets and alternative assumptions affect the variability in impacts from land and water use and LUC for production, is crucial to provide accurate estimates of environmental impacts. This uncertainty extends to predictive land use change models, where the multitude of available and often complex modelling frameworks make it difficult to understand whether differences in modelled results are due to underlying data, assumptions or models. Therefore, Hertel et al. (2019) also argued in their review that there should be more intercomparison and harmonisation between different land use change modelling approaches.

1.3.4 Bridging the gap to implementation

Despite the acceleration of research since the Millennium Ecosystem Assessment report in 2005, raised awareness and frequent conversations about sustainable development of ecosystems among decision-makers within multi-national companies and governments, implementation of this science within decision making is still at an early stage despite the urgent need to act (Ahlström et al., 2020; Guerry et al., 2015; McKenzie et al., 2014). Ahlström et al. (2020) referred to this gap as the ‘corporate-ecological disconnect’ where business practices are not based in the reality of an increasingly resource scarce world affected by increasing global risks due to climate and global environmental change. As the majority of environmental impacts of agri-commodities emerge from supply chains, measuring and managing sustainability in global supply chains is especially important (Thorlakson et al. 2018). While the science of supply chain sustainability has been advanced through improvements in transparency and traceability, data collection and additional indicators (e.g., biodiversity), converting this data into useful and actionable information for stakeholders from NGOs, multi-national companies, governments and consumers is challenging (O’Rourke, 2014). Although the multi-criteria approach of LCA makes it more suitable to support decision-making, this also makes the results more complicated to understand (Notarnicola et al., 2017). The diversity of methodologies, data and assumption has led to variable results, uncertainty and thus to confusion, threatening the credibility of LCA (Ridoutt et al., 2015).

To address complex global sustainability challenges and suggest solution options, knowledge ‘co-production’ involving academics together with non-academics has been suggested (Lang et al., 2012). This allows the incorporation of stakeholders’ needs ensuring that the developed research is useful, and empower decision-makers to act (Cowling et al., 2008). Particularly for supply chain sustainability, tools are urgently needed that can convert data into meaningful information supporting decisions of retailers, manufactures and consumers (O'Rourke, 2014). Research is needed that explicitly engages with stakeholders in companies and NGOs to identify challenges in the implementation and identify how existing decision support tool such as LCA can be improved to help in the transition towards sustainable supply chains.

1.4 Aims and contribution

Despite the urgent need to produce commodities more sustainably and the accelerated availability of data, tools and methods aiming to provide information about environmental concerns in supply chains, the implementation of this knowledge into decision-making is lagging. To bridge this gap, the overall aim of this thesis is to understand opportunities to improve estimates of water- and land use (change)- impacts of agricultural commodities linked to sub-national complex supply chain data. The specific research question of each results Chapter contributing to the overarching aim of the thesis are listed in Table 1.1.

This thesis contributes to existing research firstly by identifying the challenges in bridging the gap from science to implementation and the contrasting perceptions on data requirements from those advising end-buyers. One challenge with developing knowledge to inform decisions is to balance simplicity to avoid in-action with acknowledging the complexity required to account for long-term supply chain sustainability. Here, I chose a qualitative approach to examine with end-buyers what additional knowledge they need to take action to improve the environmental sustainability of agricultural commodities within global complex supply chains. For an in-depth exploration, I conducted semi-structured interviews and focus group discussions with manufacturers and retailers but also those actors advising them on sustainability concerns such as NGOs, consultancies and certification bodies (Chapter 2).

Secondly, this thesis seeks to respond to several of the end-buyer requirements identified, and adds value to existing research by demonstrating that environmental impacts of commodity production are not only highly spatially variable for land use change emissions and biodiversity but also for soil productivity loss and water scarcity. To demonstrate this, I linked sub-national trade flow mapping data to existing indicators of water and land use (change) impacts using spatial data analyses and

LCA principles with which many industry representatives are familiar with. For comparison across producing countries, I used consistent data and indicators across the three major soybean producing regions of Argentina, Brazil and Paraguay (Chapter 3).

Thirdly, this study contributes to existing research by identifying sources of variability and uncertainty in the estimated impacts of using water and land use (change) in commodity supply chains which will inform the ongoing debate on how to assess and mitigate the detrimental impacts of trade and agricultural production. Improving this knowledge will also help industry to navigate the challenging complexity of supply-chain sustainability and available tools, data and methods. To achieve this, I analysed the sensitivity of the estimated results to different methodological and data choices taken in the application of the LCA methods (Chapter 4).

Finally, I contribute to the methods that underpin predictive land use change models by incorporating sub-national supply chain mapping data to help understand possibilities to reduce uncertainty in modelled land use change patterns associated with different consuming countries. (Chapter 5).

Table 1.1. Summary of research questions from individual Chapters.

Chapter 2	Building on the recent sub-national supply chain mapping data that were developed to help reduce tropical deforestation, what knowledge is needed for end-buyers' decision-making to consider environmental sustainability in complex global agricultural commodity supply chains?
Chapter 3	If we incorporate sub-national trade flow mapping data and LCA principles to provide a more holistic assessment of environmental sustainability linked to current commodity production systems (specifically soybean): what do these methods tell us about the spatial distribution of supply chain impacts and their potential trade-offs?
Chapter 4	How sensitive to methodological or data choices are estimates of the impacts (and associated trade-offs) of water and land use(change) linked to sub-national soybean supply-chains?
Chapter 5	What are the implications of using sub-national supply chain mapping data in economic models that project future land use change (with an example for soybeans illustrated for Argentina)?

1.5 Structural outline of the thesis

Following this introductory Chapter, this thesis is organised as follows: Chapter 2 presents the findings of semi-structured interviews engaging with stakeholders and addressing the question of what knowledge end-buyers of ‘forest-risk’ commodities require to utilise or build upon sub-national supply chain mapping data and improve environmental sustainability in complex agricultural supply chains.

Chapter 3 builds on the insights gained about a need for a holistic environmental sustainability assessment in Chapter 2, by linking sub-national trade flows to impacts of soybean production on land use change emissions, biodiversity damage, water scarcity and soil productivity loss, consistently across three producing countries.

Chapter 4 responds to the identified stakeholders’ needs for robust estimates of environmental impacts by testing the sensitivity of the results of Chapter 3 to different methodological and data choices as well as assumptions on farming practices.

Chapter 5 relates to the stakeholder needs in terms of wanting to understand how environmental impacts might evolve in future, by exploring the effect of incorporating sub-national supply chain mapping data into a predictive land use change model.

Chapter 6 discusses aspects which were common across all previous Chapters, highlights limitations of the research in this thesis, describes what this means for future research and illustrates the implications of these findings for practice and policy.

Chapter 2 Stakeholder Interview

Sustainability challenges in complex global commodity chains: Insights from stakeholders and implications for future research

Abstract

Companies have made ambitious commitments to source agricultural commodities sustainably to protect natural ecosystems. However, identifying effective solutions to meet these commitments is particularly challenging in complex globalized supply chains. Despite rapid advances in the availability of tools and methods aiming to convert data into useful information about environmental concerns, the implementation of this knowledge into decision-making is lagging behind. There is an urgent need to find out how science could be improved to accelerate progress towards more sustainable global supply chains. Here, I explore how different stakeholders involved in shaping decision-making within globalized supply chains themselves see limitations in knowledge and barriers to progress in the specific context of 'forest risk' commodities. I present interview and focus group discussion data of manufacturers, retailers, NGOs and data providers. Stakeholders observed a need for more research and guidance on how to identify and manage trade-offs and unintended consequences across different dimensions of sustainability. But stakeholders also articulated a desire to better understand how to affect change on sustainability challenges in the system of globalized supply chains. Future research needs to identify the most effective strategies for different actors to achieve collective progress and use scarce resources more effectively to maximize sustainability outcomes. To adjust the research agenda towards one that is more useful in practice, more interdisciplinary research and closer collaboration between science, policy and business is needed, facilitated by researchers and NGOs.

2.1 Introduction

The global food system is a key source of greenhouse gas emissions (Willett et al., 2019) and the biggest driver of biodiversity loss, ecosystem conversion (IPBES, 2020), soil degradation (Pimentel and Burgess, 2013) and water consumption (Hess, 2021). It is also likely to be worst hit by climate change, natural resource scarcity and land degradation (Rockström et al., 2020). In response, multi-national companies and governments are setting targets and taking action aimed at tackling these challenges (SBTi, 2020). For many companies in the agri-food sector, however, their largest impacts on carbon and biodiversity take place within their supply chains and therefore outside of their direct control (Tidy, Wang and Hall, 2016).

Given the contribution of land use change to climate change and biodiversity loss, many multi-national companies have made commitments to eliminate deforestation and the degradation of natural ecosystems from their supply chains (Lambin et al., 2018; Donofrio, Rothrock and Leonard, 2017). The size and influence of multi-national companies means their sustainability commitments are critical (Kareiva et al., 2015). However, despite ambitious goals, deforestation rates have not reduced (Curtis et al., 2018), biodiversity loss is continuing globally (Díaz et al., 2019), and food-related greenhouse gas emissions have not reduced to levels necessary to limit climate change to 1.5°C (Willett et al., 2019).

In practice, progress on the implementation of commitments is hindered by globalisation of trade (Lyons-White and Knight, 2018), which has increased the spatial distance and number of actors between consumption and agricultural production (Liu et al., 2015; Liu et al., 2013). This complexity is making it challenging to understand the origin of products and associated impacts (Godar et al., 2015). In this context, transparency is a crucial prerequisite to identifying the different roles and responsibilities of actors in the system (Garrett et al., 2019). Many supply chains lack transparency, which is partly due to limited traceability (Zu Ermgassen et al., 2020a). Improving traceability is most challenging for commodities which are traded internationally in large quantities and have complex life cycles such as palm oil, soybean and beef (Godar et al., 2016). Progress is accelerating in improving the traceability and transparency of supply chains (Gardner et al., 2019). But, with any increase in data comes a concurrent need to make sure this is translated into actionable information for decision makers. However, understanding of how best to translate this type of data into meaningful information that can guide more sustainable decisions remains lacking (Schröter et al., 2018; O'Rourke, 2014). To understand environmental impacts linked to commodities, not only are improvements in the understanding of commodity origins required but also improvements in the measures of the impacts taking place within production regions.

An increased interest in the measurement and analysis of the consequences of decisions in product design and procurement on the natural environment has led to the emergence of Life Cycle Assessment (LCA) and product 'footprinting' as prevailing approaches. These approaches have been applied to translate data into useful information to support manufacturers and retailers (Wiedmann and Lenzen, 2018; Othoniel et al., 2016; Hellweg and Milà I Canals, 2014). However, improving regional detail and the robustness of environmental impact metrics to increase their relevance to consumers and producers remains a challenge (Lee et al., 2020; Chaplin-Kramer et al., 2017; Hellweg and Milà I Canals, 2014). Recently, advances in scientific understanding, computing, visualisation and data availability have allowed a number of improvements: Firstly, the ability to widen the sustainability concerns that can be considered such as carbon emissions (Escobar et al., 2020), biodiversity (Verones and Moran et al., 2017; Chaudhary and Kastner, 2016; Mueller, Baan and Koellner, 2014), water scarcity (Boulay et al., 2018, 2018; Hoekstra and Mekonnen, 2012) and soil erosion (Sonderegger, Pfister and Hellweg, 2020, 2020; Stoessel et al., 2018). Secondly, enhanced accounting of spatial heterogeneity in environmental characteristics at sub-national level (districts, provinces; e.g. (Lathuillière et al., 2021; Green et al., 2019; Flach et al., 2016). Thirdly, regular updates linked to changes in environmental state in production landscapes through the integration of near real-time earth observation data to monitor progress (Harris et al., 2021). Importantly, this information is now relatively accessible to end-users, including via publicly available platforms such as Global Forest Watch (Global Forest Watch, 2020), Water Risk Filter (WWF, 2020) or Trase (Trase.earth).

However, despite these advances, implementation into decision-making is slow (Guerry et al. 2015). There is a lack of urgent, large-scale transformative change in corporate practice required to stay within a planetary 'safe operating space' (Folke et al., 2019). This has been referred to as an 'ecological-corporate disconnect' (Ahlström et al., 2020). In the literature, several factors have been described that help explain why improved knowledge has not resulted in improved implementation: A lack of academic ability to develop science that is applicable in practice (Ahlström et al., 2020); an 'explosion' of data and information about sustainability and supply chains that has the potential to lead to further confusion and resultant in-action (Gardner et al., 2019); the challenge inherent in ascribing responsibility to various actors along complex value chains from producer to consumer, which limits the ability for an individual stakeholder to undertake meaningful change (Eakin et al. 2017). There is also debate in the scientific community about how much simplification is required to translate complex information into guidance for decision-makers (Schindler, Graef and König, 2015).

To tackle the complexity inherent in such systemic problems, it has been suggested that a more inclusive approach is needed that incorporates the perspectives and influence of multiple stakeholders (DeFries and Nagendra, 2017). Additionally, Schröter et al. (2018) have argued that research on interregional sustainability at the science-policy interface should focus on determining the level of detail that is possible based on current data availability but also necessary to inform policies. As an approach to bridge the gap between science and action on sustainability, *co-production* of knowledge is gaining popularity (Schneider et al., 2019). Hereby co-production is defined as ‘a *contribution of multiple knowledge sources and capacities from different stakeholders spanning the science–policy–society interface with the goal of co-creating knowledge and information to inform environmental decision-making’* (Djenontin and Meadow, 2018). Additionally, social-ecological systems (SES) thinking is a potentially useful concept to help bridge the divide between science and corporate sustainability practice (see e.g. Ahlström, Williams and Vildåsen, 2020). In the context of food, systems thinking focuses on the interactions and dynamics between the system’s different components along the entire value chain (TEEB, 2018b).

This paper describes a co-production process which through stakeholder interviews aimed to identify – from the perspective of end-buyers (here, manufacturers and retailers) – the primary motivations that end-buyer companies have to measure their environmental sustainability, which methods or data they have available and particularly the limitations they experience with existing data, methods and tools in their application to decision making. The focus of this study is on how sub-national trade flow data enabled by increases in transparency and traceability can be used to improve the spatial granularity of existing footprinting and LCA approaches. I also wanted to determine what emerging sustainability concerns these end-buyers have which are not currently adequately supported via the provision of sustainability information. Finally, I explore what future research could focus on to ensure that decision-makers can have greater confidence that their actions will lead to positive sustainable outcomes via the identification of trade-offs, synergies and unintended consequences of decisions.

2.2 Methods

2.2.1 Primary Data Collection

Through qualitative data gathering methods I wanted to gain rich and in-depth understanding of the different perspectives of various stakeholders along complex supply chains. 20 semi-structured interviews and two focus group discussions (FGDs) were conducted (Table 2.1; Figure S 1.1; Table S 1.1). Initial interviewees were selected based on their ability to provide meaningful insights from their professional experience within consumer-facing companies like manufacturers and retailers. First, I interviewed manufacturers and retailers about their specific information needs and underlying motivations (Phase A in Table 2.1; **Figure 2.1**). An insight from this first phase of engagement was that their motivations and concerns were in part shaped by NGOs who act as advocates for their decision-making (see Figure 2.2). I therefore also interviewed selected relevant NGOs (Phase B in Table 2.1). Thirdly, as it was revealed that NGO's themselves depend on others to provide information[1], I then talked to consultancies and certification bodies involved in gathering data in the supply chain (Phase C in Table 2.1). By adopting this iterative interview process, I was able to narrow down the core issues acting as barriers to implementation, develop an understanding of the research gaps most relevant to practice (described by companies and NGOs) and feasibility depending on data availability (determined by consultancies and certifiers). Interviews and FGDs lasted 30-60 minutes depending on the availability of the participant and usually took place via phone or Skype/Zoom, with some in-person. The purpose of the interviews was sent in written format to participants in advance of the meeting with interviewees also be offered anonymity (see Table 2.1 for abbreviations used here). Primary data collection took place between January and May 2020.

[1] International NGO representative, conference call (7 May, 2020)

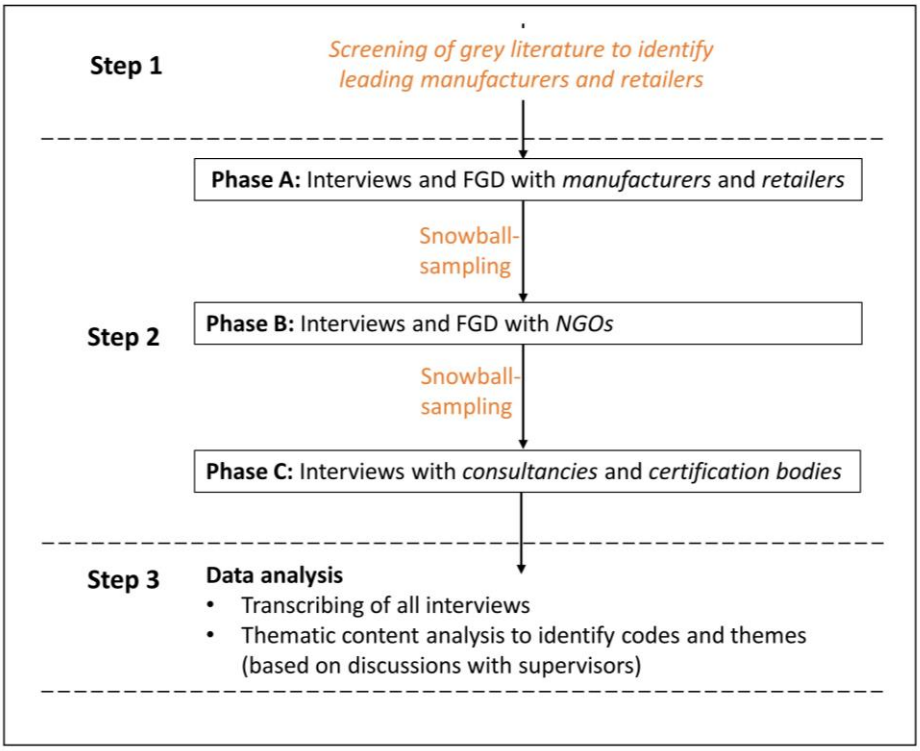

Figure 2.1. Process flow diagram describing the steps taken to identify participants (in orange), gather data and analyse the data.

Table 2.1. Overview of interviews and focus group discussions (FGDs) conducted

Type of actor		**Number and type of data gathering method (interviews/FGDs)**	**Number of organisations**	**Number and type of participant**
Phase A	**Companies**			
Manufacturers (M)[2]		5 interviews and 1 FGD	4	6 (Sustainability Manager/Director, Sustainable Sourcing Manager/Director)
European retailer I		5 interviews	5	5 (Sustainability Manager, Sustainable Sourcing Managers, CSR Manager)
Phase B	**NGOs**			
European-centred NGO		3 interviews	3	3 (Program Managers)
Global NGO (N)		1 interview and 1 FGD	1	4 (Sustainability Directors, Program Managers)
Phase C	**Data providers**			
Consultancies I		4 interviews	4	4 (Sustainability Consultants, Partner)
Certification bodies (CB)		3 interviews	3	3 (Program Managers, Director)

Note: To ensure anonymity, names of specific organisations were omitted.

Relevant manufacturers and retailers for Phase A were identified through their use of certification standards (such as the Roundtable on Sustainable Palm Oil (RSPO) as mentioned on publicly available websites (Donofrio et al., 2017), commitment to science-based greenhouse gas emission targets including their supply chains (SBTi, 2020), their association to the food and beverages sector and sizeable market share (and therefore responsibility). Snowball sampling (Patton, 2015) was then used to identify further relevant interviewees, particularly in Phase B and C (see Table 2.1). Interviews and FGDs were both semi-structured (guided by six open-ended questions) which allowed flexibility to ask further follow-up questions depending on the existing knowledge or experience of the interviewee (see Fielding and Thomas, 2012; and section S.1 Supplementary Information Chapter 2).

[2] Abbreviations of types of actors used throughout the publication to anonymise interviewees

2.2.2 Data Analyses

Interview and focus group transcripts were coded by the lead author into broad categories. In a second round of more in-depth coding, findings were further classified into major emerging themes (Fielding, 2012). These themes included motivations, specific sustainability concerns, type of action/decisions, unintended consequences and limitations of existing methods and barriers to implementation. An overview of the detailed codes and how they relate to the themes can be found in Table S 1.3 in the Appendix. I used thematic content analysis to iteratively refine themes and codes (Whiteman and Cooper, 2016) based on research team discussions (Cortner et al., 2019). A general inductive approach to analyse the qualitative data has been applied (Finfgeld-Connett, 2014) to allow flexibility to find themes or codes in the raw data which were not pre-defined. In the analyses and interpretation of the data, I paid particular attention to the similarities and differences in the perceptions between the different types of actors (see Baldy and Kruse, 2019).

2.3 Results and Discussion

Interviewees were asked to consider what environmental sustainability concerns within producing countries end-buyers perceive as relevant for their own organisation. In particular I was interested in their views on approaches or solutions to bridge the gap between knowledge and implementation of activities to address these sustainability concerns. Section 2.3.1 presents the key themes from my data analyses on the motivations and drivers of end-buyers to take action on sustainability challenges in globalised supply chains. Section 2.3.2 describes the key decisions for which more robust scientific evidence is needed to support end-buyers. Section 2.3.3 focuses on the areas for which end-buyers would like to have more scientific evidence to ensure their decisions are sustainable in the long-term. Section 2.3.4 focuses on understanding the specific limitations of the existing science in supporting decisions of end-buyers. Section 2.3.5 considers how collaboration to tackle systemic challenges can be supported through science. All findings are discussed in the context of previously published scientific literature. I use quotes from the interviews to illustrate the most pressing knowledge gaps and concerns identified among different stakeholders.

2.3.1 Motivations for end-buyer companies in sub-national environmental sustainability information

To identify the knowledge that would be most useful to guide decision-making, I first wanted to understand why downstream companies in the agri-food sector want to understand the origin and associated environmental concerns of their commodities. During the research, it became clear that the motivations depend on the location of companies along the supply chain, their size and consumer audience. However, four main motivations were most prominent: (1) Pressure from Western NGOs, (2) internal motivation to do the 'right' thing and thereby retain and attract employees, (3) securing future supply and (4) investors wanting to reduce their risk.

My interviews suggest that the motivations of end-buyers are influenced by NGOs, as illustrated via the response from a representative of one retailer: *"Do I really care where in North America it's from at the moment? […] No, not really cause there's no one in civil society or NGOs that's really telling me that there's a problem [related to deforestation]"* (R4). A similar role has been ascribed to NGOs in global economies as a 'watchdog' to point out non-ethical behaviour (Weber and Partzsch, 2018). Among manufacturers, who are closer to production and demonstrated longer-term thinking, ensuring security of supply in future becomes relevant additional to other factors such as price and quality. As one manufacturer explained:

> *"As […] a company that depends on agriculture we have to be aware of what our [environmental] impacts are and we have to work to mitigate them if we want to be prepared for the future states of the world and food growing in the world"* (M1)

In my reading, therefore, the underlying motivations of companies are shaped both by science but also by the influence of NGOs present in the societies in which these end-buyers are operating in (see Figure 2.2).

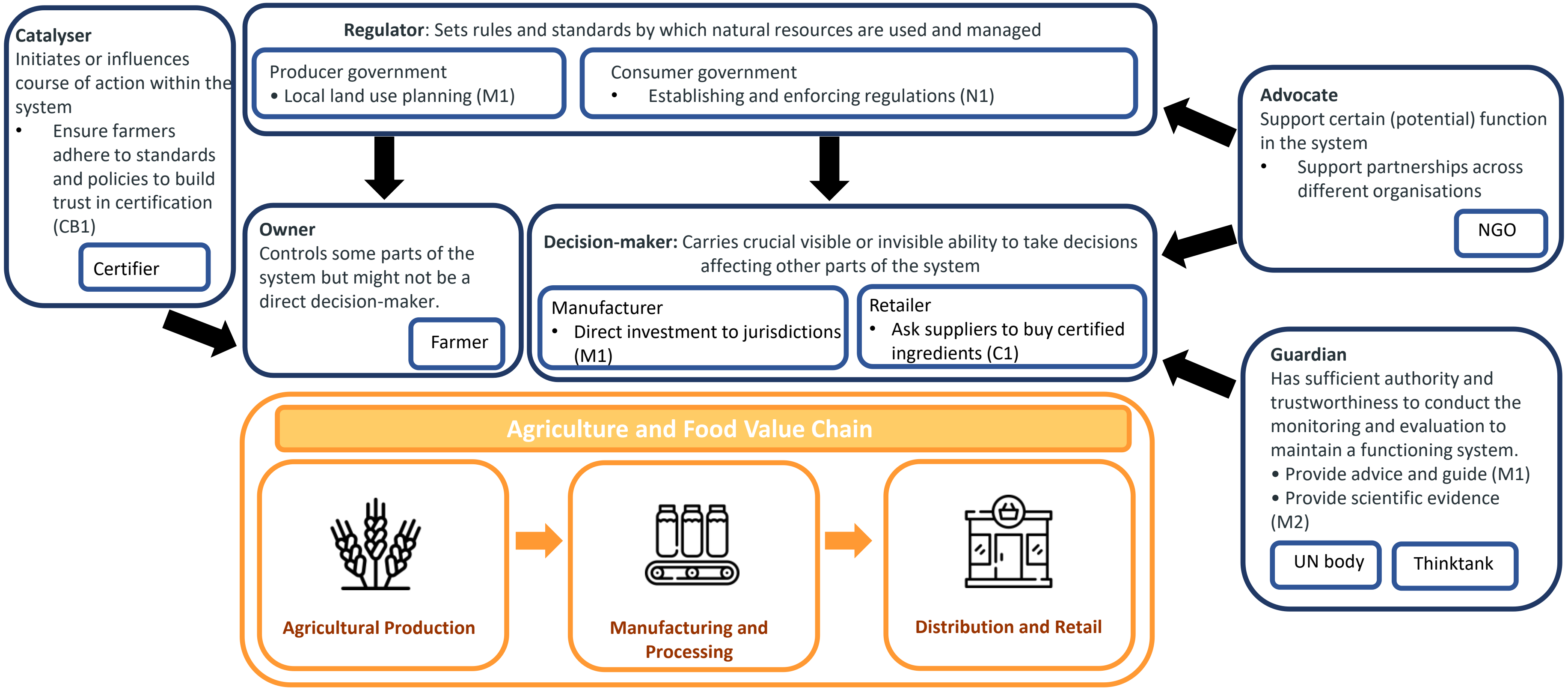

Figure 2.2. Roles of different stakeholders within the global food system (adapted from Lyon et al., 2020) to tackle sustainability challenge, type of organisation and examples of actions taken compiled by author.

2.3.2 Solutions which need more support from scientists working on supply chain transparency, traceability and associated environmental concerns

2.3.2.1 Commodities traded in complex supply chains

The more complex a supply chain, the more actors sit between the end-buyer and the producer and thus harder it is to get reliable information on the origin of the trade flows. Knowledge of the origin of supply chains is, however, crucial to identify effective strategies to manage sustainability challenges (Gardner et al., 2019). All end-buyers that I interviewed in this study mentioned that they require external traceability information especially for 'hidden' commodities like soy, palm oil and sugar. This was described by one manufacturer as: "*embedded soy for chicken and beef. If [trade flow models] could unpick that, that would be super helpful. Because those supply chains, we're always very much a distant end user of by-products*" (M1). In contrast, interviewees explained that for less processed products such as coffee, cocoa or tea, supply chains are shorter and less complex and thus it is easier to get the information they would like to have through engagement with their own supply chain. Most manufacturers mentioned that they have to prioritise their sustainability activities depending on which products are most important for their business[3]. The level of detail they require on the origin of the commodity also depends on perceived concern within the region in the world where it is produced, as one manufacturer illustrated:

> "*corn that's grown in the United States: we can probably classify that as a pretty low risk that we don't need to worry too much about and we don't therefore need huge great controls in place to manage the sustainability of that production. It's also from a country that's got probably a lot of controls and checks in place already*." (M4)

In my interpretation, this illustrates that a need by end-buyers for better information about the sustainability of agricultural practices depends on the sourcing region and the commodity in question.

2.3.2.2 Certification to improve production practices

Most end-buyers see certification systems like RSPO, Roundtable on Responsible Soy (RTRS) or company-internal schemes as important tools to manage their risks. Some companies showed a deep trust in these schemes as illustrated by one retailer: *"I don't need to risk map that because I know that the supplier is going to have to source it on Fairtrade terms"* (R1). However, other

[3] International NGO representative, conference call (May 7, 2020)

respondents were more critical and aware of the limitations of certification, as illustrated by one manufacturer:

> *"If you look at [company internal certification], for example all of the RSPO things: They are all about the action you should take, and not measuring the outcomes of those actions. So, there is then the belief that sustainably sourced equals better or lower impact; that's not necessarily proven."* (M2)

Also, all consultants were aware of at least some limitations of certification as a means to improve sustainability. As illustrated by one consultant:

> *"Actually, they [end-buyers] buy RSPO. Then RSPO is not available for others. Then it doesn't change anything. Plus, if you actually look at what's happening in Indonesia then: 'Okay, there's RSPO certified palm oil'. But then you have these mass balances and you actually don't know where the food comes from and whether there was deforestation and so forth."* (C4)

We interpret these quotes to mean that certification is commonly used – despite the recognised limitations – because many end-buyers find it straightforward to affect change on choices that are under their direct control (e.g. asking suppliers to buy certified commodities) in comparison to attempting to exert influence multiple tiers down the supply chain. Additionally, certification can be used as explicit evidence to their external stakeholders that they are taking efforts to improve the environmental sustainability of their supply chains. In this regard, research could help to provide end-buyers with alternative approaches besides certification to evidence the sustainability outcome of their efforts.

2.3.2.3 Directing investment in landscapes

To promote more sustainable production, actors need to know where, when and what to do about problems to ensure that their efforts actually lead to long-term sustainability outcomes. To understand which geographic areas are in particular need of enhanced attention, supply chain transparency can be helpful (Gardner et al., 2019). However, among interviewees there was debate about how much traceability is needed to affect sustainability benefits of commodity production. As one international NGO commented *"You need maybe to stop putting so much money in traceability and put more money in a landscape in and try to drive some change in a geography"* (N1). Several NGOs, manufacturers and retailers I interviewed saw directing investment into certain producing regions as a promising solution to improve environmental sustainability. As one retailer commented:

> *"There's nothing you can do about it because it's legal deforestation anyway and the only way you are going to stop that is the financial incentive and that's why we made this […] announcement in the Cerrado[4] region in Brazil"* (R4)

Several NGOs agreed with this statement about the importance of financial compensation to reduce deforestation "*while we still have something that is more profitable than keeping the forests, we will have deforestation" (N1).* However, information is then needed about which regions are best to invest in, as otherwise – as one interviewed consultant warned – "*the unintended consequences might be rather that they [end-buyers] invest in the wrong place*" *(C4)*

The quotes suggest that, to make landscape or jurisdictional approaches 47ork47utive, there needs to be careful attention put to ensuring that their pathway to implementation is not limited by the same pitfalls of current commodity certification systems. One of the consultants I spoke to saw landscape approaches – because of similar limitations as certification – only as an intermediate step towards a more effective alternative[5]. Certification is limited by a lack of rigorous enforcement and monitoring but also a scarcity of empirical studies measuring the impact of certification on sustainability outcomes (Furumo et al., 2020). To be able to identify if the investment leads to sustainability outcomes it needs to be clearer how practices would be encouraged, progress monitored and performance measured. Providing data to regularly monitor performance at low cost remains a challenge.

2.3.3 Priority concerns

2.3.3.1 Environmental sustainability: Balancing need for complexity with simplicity

The environmental sustainability concerns most frequently mentioned by interviewees linked to commodity sourcing were greenhouse gas emissions, deforestation and ecosystem conversion, biodiversity loss and water consumption. Opinions on a need to consider multiple sustainability concerns in contrast to focusing on a single concern varied between stakeholders. Whereas some interviewed NGOs, retailers and consultancies argued that out of pragmatism more simplicity is needed, others thought that multiple sustainability concerns should be considered together to

[4] Ecologically important savannah ecoregion in Brazil
[5] Consultant, representative, conference call (April 29, 2020)

avoid unintended consequences. One consultant stressed the simplification in which sustainability was taken forward by many retailers in Europe: *"I think largely to the climate change agenda that's been really simplified and in terms of environmental sustainability most retailers we work with […], that's now only just collapsed down into deforestation"* (C1). Besides the interest in carbon and deforestation, one NGO representative noted that there is a focus on more visible and more fast-changing issues such as deforestation[6] which can be easily and cost-effectively monitored with satellites. However, in my view, there is a risk that adopting too short-sighted an approach could have potential consequences on less visible and slower-changing sustainability challenges such as soil degradation or biodiversity loss that scientists have been warning about for years (Davies, 2017; Rockström et al., 2009). Scientific experts have cautioned about over-simplification[7] which was acknowledged by some end-buyers who recognised the need to embrace some complexity; as one retailer stressed:

> "a*ny kind of methods that combines several sustainability aspects is good. Because otherwise you sit with different tools for every different type of aspect. So, I also understand that there's a bigger complexity the more aspects you include, but if you manage to do so, it becomes a more valid tool"* (R3)

Most stakeholders who argued for a need for simplicity justified this by the risk of complexity leading to inaction. This challenge of balancing complexity while avoiding inaction was stressed by one retailer:

> *"we are entering sort of an era where we have gone from trying to really make the complex super simple […] just to be able to do something because if we make it too complex then we […] don't dare to do anything. But I think we are entering from that simplification era to actually […] acknowledge that this is a complex situation"* (R3).

Similarly, the influential science-based initiative 'EAT Lancet' (which is aiming to transform the global food system) argues that: *"We need to become better at embracing complexity while reducing the desire to oversimplify everything."* (Willett et al., 2019). Quotations from each stakeholder illustrating the level of desired complexity in decision-support tools for the food system

[6] NGO representative, conference call (April 7, 2020)

[7] See e.g. Interview with Scientific Director of EAT Lancet, (11 October 2019) https://www.uu.nl/en/research/future-food-utrecht/interview-with-fabrice-declerck

can be found in Table S 1.3. However, opinions about the level of complexity end-buyer companies can handle varied among stakeholders depending on company-internal expertise and capacity[8],[9].

2.3.3.2 Beyond environment: social sustainability

When stakeholders were asked which other issues they are concerned about, the majority mentioned social issues. Social sustainability aspects came up in most discussions even though I had stressed at the beginning of the interviews that these would be out of scope of my own research. One representative of a certification body explained the importance given to social aspects by European end-buyers: *"I think there are two big issues when a company starts the process of certification. First, they want to solve the risk of deforestation in their supply chain. After that, they are asking about social aspects, like poor communities' projects, improvement labour conditions and biodiversity on the farm."* (CB1) Therefore, end-buyers of commodities have the desire to consider environmental aspects together with social issues. Indeed, sustainability concerns in producing regions were often considered as interlinked, with for example water pollution from agriculture noted as affecting downstream drinking water quality, poverty and education affecting knowledge and the ability to manage land sustainably. This perspective is illustrative of social-ecological systems thinking, as described by Ahlström et al. (2020). In this respect, a trade-off between social and environmental issues can arise. This dilemma was illustrated by one manufacturer:

> *"The social versus the environmental trade-offs are the biggest ones […] But we find that if we stop doing business to them, the consequence to vulnerable people either working for that business or linked to that business would be so great that we may still have to work with that business. Because if we would stop doing business with them, the vulnerable people would be even more vulnerable."* (R4)

2.3.4 Limitations of existing science and tools to advance sustainability

2.3.4.1 Scale: focus on own supply chain vs affect change at scale

The focus for companies aiming to tackle environmental sustainability in their supply chain varied. In contrast, to representatives from manufacturers who were focused more on efforts to change practices in their own supply chains, interviewed retailers showed less focus on their own supply

[8] Manufacturer representative, conference call (February 14, 2020)
[9] Retailer representative, conference call (February 26, 2020)

chains but instead rather focused on collaborative efforts to reduce deforestation[10]. Retailers are more distant from producing regions than manufacturers, and thus traceability data to producing regions is harder to obtain. Therefore, a focus to affect change through collaborations is pragmatically more feasible. The manufacturers' emphasis on their own supply chain allows them to provide evidence and report progress against the environmental commitments they set themselves. A statement from one manufacturer supports this: *"being able to prove to the world that you are actually eliminating deforestation from your supply chain that there is actually stuff going on there that you can measure and count and report against."* (M4)

Consequently, what some of these companies *"end up doing is buying all their palm oil from concessions that were cleared 20, 30 years ago: So of course, there is no deforestation"* (N4). However, this would not reduce the overall deforestation in the world as other companies with different priorities might buy commodities grown on recently deforested land. Therefore, some NGOs I interviewed do not believe that a focus on companies' own supply chains alone is an effective solution to tackle a challenge like deforestation[11]. Other NGOs ask end-buyers to provide evidence of no deforestation in their entire supply chain, as highlighted by a comment from an NGO:

> *"So, it's a really, really tricky balance for companies who we are asking two things: You have to be squeaky clean but you also have to work in tough places you can't just [buy from long deforested places]. So, what should they be doing: they should be doing both: making sure that their supply chain is clean and driving clean suppliers."* (N4)

A focus on the own supply chain requires much more detailed traceability data and segregation in supply chains. However, ensuring traceability and segregation is costly and ultimately financial resources should be directed to where the sustainability outcomes can be maximised. However, providing cost-effective evidence on the outcomes of actions seems to be a challenge, as one manufacturer explained: *"there's generally a total lack of evidence in terms of impact and performance. I don't find that difficult to understand because the cost of these sorts of things is enormous"* (M2). Therefore, as long as some NGOs ask end-buyers to both provide evidence of their own supply chain but also contrIbute to affect change at scale, science needs to support both of these purposes.

[10] Retailer representative, conference call (March 12, 2020)
[11] International NGO representative, conference call (April 16, 2020)

2.3.4.2 Temporal scales

The dynamic nature and complexity of supply chains provides a challenge for data providers to generate reliable information which is still available quickly enough to inform current decisions. Many trade flow datasets, for example, are subject to data lags. In the context of commodity-linked sustainability, this limitation of providing recent enough trade flow data was pointed out by multiple end-buyers and consultants. As one consultant explained:

> *"A lot of the information and the metrics that are available have […] issues with […] time-lag: a lot of the data that is used is very static. So, something like Trase is not really that useful to have something that happened last year. You could have accepted hundreds of tons of deforestation associated into your supply chain before the next version of Trase or things that have that sort of slow renewal time come out."* (C1)

However, having more recent data is not automatically useful as one NGO representative pointed out:

> *"they [end-buyers] see in their new real time monitoring system that in the surrounding of the units where they buy from forest is being cleared. But what do you do with that information? First of all, it's not linked with your supply base because at the time that the tree is being cut down, there is nothing going there. So, it is not within your supply base. […] And secondly […] as long as there is no one on the ground [from the end-buyer company] to investigate and to do something about it and to understand the drivers it's impossible to stop deforestation."* (N3)

One reason for the time-lag in providing trade flow data is that currently the processing and cleaning to ensure robustness is time-intensive for researchers (see Croft et al. 2018). However, ensuring robustness of the provided information is important to build trust and reliability to ensure uptake by users in their decisions. Analysis by Reis et al. (2020) found that the stability and consistency in regional trade flows, referred to as 'stickiness', may vary, with some remaining relatively consistent over time and other supply chain relationships changing rapidly. Researchers will therefore need to find the right balance between accurateness and timeliness of the provided information depending on the purpose of the intended users. Additional detailed information is costly and it is questionable how much detail is needed in an uncertain world as one manufacturer pointed out:

> *"I can pay vast sums of money and spend huge amounts of time, but will the quality of the answer be any better than a screening type of approach, given the level of uncertainty that exists in the data and the level of changes that are likely to occur?"* (M2)

With respect to changes in future, two interviewed manufacturers[12,13] mentioned that they believed that to prove the origin and manage associated sustainability issues, closer, longer-term relationships with producers will become more important, and thus trade flow stickiness will increase (see Reis et al., 2020). This may also reduce the complexity of supply chains as there would potentially be fewer intermediaries between manufacturer and producer.

2.3.4.3 Meaningful metrics

Several end-buyer companies mentioned that they would like to link trade flow information to metrics in which they are already using or might in future use to report their environmental performance. Since the Paris Climate Agreement, hundreds of companies have committed to Science Based Targets for climate (Rockström et al., 2020). For companies in the food sector, most greenhouse gas (GHG) emissions occur during the agricultural stage, and it is therefore expected that the interest in methodologies to measure Scope 3 emissions (i.e. supply chain) will increase in future (Tidy et al. 2016). This speculation was supported by one retailer's comment:

> *"carbon impact is relevant especially in the future where more and more companies will be setting Science Based Targets and clear their scope 3 emissions in the supply chain. […] I know that some retailers are already doing that and I imagine that we at some point will as well look into that."* (R5)

Another knowledge gap that was brought up in the interviews was the interaction between different spatial scales. Manufacturers in particular mentioned that they would like to better be able to understand how interventions at farm- or plantation scale would relate to landscape scale changes and ultimately impacts at global scale[14]. In an ideal world, methods would be able to sum up how interventions at the farm-scale would stack up with changes at landscape scale and ultimately global scale as many companies' supply chains and commitments are global[15]. This would help to identify which interventions at which scale would be most effective to meet their

[12] Manufacturer representative, conference call (February 13, 2020)
[13] Manufacturer representative, conference call (January 20, 2020)
[14] Manufacturer representative, conference call (February 13, 2020)
[15] Manufacturer representative, conference call (February 14, 2020)

environmental targets: for example, improving agricultural practices at farm scale, land use planning at landscape scale to reduce ecosystem conversion, or changes in the design of products?

2.3.5 Collaboration to tackle systemic challenges

All manufacturers and retailers I interviewed described feeling that they have limited leverage to affect and evidence meaningful change through their supply chain commitments because their globalised complex supply chains were outside of their direct control. Examples of commitments (see Donofrio et al., 2017) are the support of no-deforestation, no-conversion on peat and reduction of greenhouse gas emissions in supply chains. Considering their commitments (see Forest Trends, 2021), and the responses of companies to my questions, it becomes clear that their ambition is to affect change at the system level. No actor alone can achieve meaningful change at system level particularly in globally traded complex commodity systems. Taking a 'systems thinking' view requires acknowledgment that there are interconnections between the system's different components, dynamic feedbacks and no single 'solution' (TEEB, 2018b). Agri-food systems are complex and characterised by interactions of multiple actors (Ingram et al., 2020). Identifying effective partnerships between different actors requires understanding their different roles in the system and the relationships between them. As one international NGO representative commented:

> *"The way at least I see it […] is that the more clarity we have on each supply chain actor responsibility and capability, the easier it will be to attribute and to share the responsibility across a supply chain."* (N1)

As previously highlighted in this study, there are different actions that different stakeholders can take to transform the food system towards progress on achieving common goals. Most of the interviewed retailers, manufacturers and NGOs saw producing governments as having one of the most influential roles to set regulations and enforce compliance around the sustainable use of natural resources. This is in line with previous research by Seymour and Harris (2019). However, they also saw this as subject to change depending on the priorities of the producing country's government. One of the European retailers I interviewed was cautious and saw their only possibility to reduce legal deforestation through providing financial incentives to compensate for the loss of economic opportunity:

> *"we are not prescriptive in terms of saying here is the solution because of their country and their own industry. But we recognise we have a role to play as a company that ends up using*

> *the soy in our supply chain. We can be part of the solution, help fund the solutions, even though they are the ones that need to take ownership of it locally because where we can't be seen as dictating the terms cause countries especially in Brazil are very sensitive about their sovereignty"* (R4)

This illustrates that, within the system, goals need to be negotiated between different actors (here producing governments and retailers). Academia and think-tanks can play a role to bring multiple stakeholders together to identify common goals and effective solutions to achieve them (Figure 2.2).

When taking a systems approach, providing evidence on unintended consequences is crucial but also seems harder to provide for end-buyers. A desire to better understand unintended consequences of collaborative efforts was brought up by multiple stakeholders. A frequently mentioned example of unintended consequences was leakage of land use change to other ecosystems, as one retailer pointed out:

> *"We have the Amazon Moratorium that drives leakage to the Cerrado. If you do the Cerrado Conservation mechanism: Is that gonna drive leakage to the Gran Chaco? And then if you're saying your soy is deforestation-free within the specific geographic bounds where it's happened but is it in the wider sense?"* (R5)

2.4 General discussion

The research needs identified within this study relate to the core challenges experienced by key stakeholders in making progress on environmental sustainability. I observed that end-buyers would like to consider multiple dimensions of sustainability together to identify trade-offs and unintended consequences. Additionally, this study illustrated multiple types of stakeholders need to be engaged in the research problem identification stage to identify what is feasible data-wise but also what advocates in the system would advise end-buyers to do. The findings identified in this study about how to bridge the gap between data science and implementation towards sustainability of global supply chains reveal a need to take a more systemic view to incorporate the complexity in the 'agri-food system'. This has implications both for science and practice which I will now discuss in the context of existing research.

2.4.1 Implications for science

To bridge the gap between science and implementation for sustainability in complex global supply chains, I see the following priorities that future research should focus on: Firstly, given the challenge of tackling sustainability in the global food system, the relevance of the research could be improved by more collaboration across different disciplines within academia but also with stakeholders outside of academia. As multiple manufacturers and retailers would like to have more guidance from experts on how to deal with trade-offs between different sustainability challenges, this would require scientific experts from different disciplines working together to develop consistently applicable methodologies that allow joint consideration of issues like biodiversity, greenhouse gas emissions, water or soil impacts. In general, the need for more interdisciplinarity within academia to help tackle sustainability challenges have been highlighted before, for example in a study aiming to identify research priorities for the palm oil industry by Padfield et al. (2019). However, these authors neither apply a qualitative approach to engage with stakeholders nor did they include end-buyers distant from producing regions. However, as illustrated in mystudy, it is important to understand in depth how those distant actors – as users of supply chain-linked risk or impact data – make decisions within an uncertain and complex system and how science can help to guide those decisions.

As expressed by the interviewees, end-buyers would like to know what actions they can take to meaningfully address sustainability within globalised complex supply chains. To better contribute to system transformations, Nielsen et al. (2019) argued that land systems science should better acknowledged the normative aspects which could be incorporated through co-production. A challenge here can be a conflict in norms between different stakeholders (DeFries and Nagendra, 2017). In this study there was a divergence in viewpoints about ecosystem protection between producing governments (want some tropical deforestation) and consuming end-buyer (no tropical deforestation at all) that differences in underlying norms could explain.

Here, more dialogue between different stakeholders guiding end-buyers (e.g. NGOs, consultancies, scientists) on feasible solutions could help. For example, identifying a trusted non-profit organisation which brings multiple stakeholders together to align their actions to achieve a common goal (role of ‘broker’; see Figure 2.2). Think-tanks having trustworthiness and authority could then help by developing monitoring tools (e.g. Global Forest Watch, 2020) to verify outcomes of activities (role of ‘guardian’; see Figure 2.2). Therefore, this study confirmed that a co-production approach, characterised through a process of mutual learning between researchers and actors in society (Lang et al., 2012), helps to identify the research gaps that are most pressing in practice. Especially as I found that decision-making of end-buyers is shaped by multiple types of organisations they trust. The flexible, iterative, approach I adopted in my interview protocol, has the benefit of incorporating the views (after the initial data collection stage (Phase A, Table 2.1) of those stakeholders that are most influential within the networks of individual end-buyers. However, a challenge of multi-stakeholder engagement is that it is a time-intensive process and the question is how this could be made more economically viable. Increasingly funding organisations and research programmes (e.g. Global Land Programme, Future Earth, Horizon Europe; EC, 2020a) are asking for co-production approaches to tackle complex real-world challenges (Schneider et al., 2019). The potential of co-production to help solve societal problems could be enhanced by more researchers discussing best practices and lessons learned about which stakeholders or representatives of stakeholders to include for which sustainability challenges, depending on the scale and geographic distance between actors. Ultimately this would also require more researchers trained in engaging with non-academic stakeholders. However, given the limited time researchers have available for engagement processes, a more effective approach might be to have non-academic organisations involved in regularly updating data and providing a more user-friendly and engaging format for scientific information. In this respect, consultancies or thinktanks could become 'impact extenders' (Goodman, Korsunova and Halme, 2017) focusing on communication of credible scientific information to non-experts.

To bridge the gap between science and implementation, Guerry et al. (2015) argued that robust evidence is needed that clearly link decisions to impacts on the environment. Improvements in the traceability of trade flow data will help to identify the origin of commodities (Gardner et al., 2019). However, as interviewees in this study reported, end-buyers would also like to understand the consequences of their decisions on the environment and therefore more forward-looking approaches are needed. This aligns to what O'Rourke et al. (2014) already pointed out in their review about the science of sustainable supply chains, that instead of a 'policing' of supply chains, more focus should be on how data and tools could be used to be more predictive and avoid unsustainable practices before they happen. Additionally, to prevent unintended consequences, a more holistic approach to sustainability is required. Interviewees in this study pointed out that there is a focus on more visible and faster changing sustainability challenges such as deforestation. Instead, data collection efforts could focus on currently less visible and slow changing issues rather than improving the detail of already visible issues.

To reduce barriers to adoption, there is a need to harmonise and align different approaches but also to find consensus among researchers about the 'best' approaches, data and methods depending on the intended purpose. Standards have been agreed on how corporations can calculate and report science-based targets including supply chains for greenhouse gas emissions (e.g. Greenhouse Gas Protocol)[16]. However, as the agri-food sector contributes considerably to other sustainability challenges such as biodiversity loss, water scarcity or water pollution, methodological advances are needed to allow corporations to quantify and report science-based targets for other major sustainability challenges as well, as Rockström et al. (2020) have argued. Initiatives are underway to develop science-based targets for some issues, such as land or biodiversity[17] lead by Science Based Targets Network (SBTN, 2020). However, it is important that these build on the latest science and be consistent with existing approaches. Without agreed and standardised methodologies, there is the risk of confusing decision-makers and practitioners, leading to inaction or even a loss of trust in scientists (Ridoutt et al., 2015). However, as science in this field is rapidly advancing and new data are becoming available, the developed methodologies also need to be flexible enough to incorporate science and data developed in future. This requires continued exchange between scientists, practitioners and tool developers.

2.4.2 Implications for practice

The dynamic interactions between different sustainability challenges illustrated in this study highlight the complexity of decision-making within sustainable production and consumption systems. As globalisation of traded commodities increases the spatial distance between them (Liu et al., 2015) it is challenging for end-buyers to understand the local context in which the farmers producing their commodities operate in. Therefore, it is difficult to understand local socio-economic drivers of sustainability concerns but also unintended consequences resulting from activities. Often there are multiple suppliers between the end-buyer and the farmers making it challenging to respond to a sustainability priority from a distance. Additionally, political boundaries are crossed where different political institutions are responsible for regulating natural resource use. What is a priority for local stakeholders will depend on the regional context (Bager et al. 2021). This context dependency also helps explain why stakeholders disagree on solution pathways. For example, one stakeholder might aim to improve smallholder livelihoods whereas another stakeholder might aim to reduce deforestation linked to their supply chain. This mismatch in priorities is typical of

[16] https://ghgprotocol.org/
[17] https://sciencebasedtargets.org/sbt_events/project-launch-science-based-targets-for-forest-land-and-agriculture-flag-related-sectors/

'systemic' environmental management problems (Larsen and Nilsson, 2017). My study suggests that to achieve meaningful progress on global sustainability challenges, more collaboration is needed across different companies (e.g. traders, growers, processors and retailers) but also between companies and different types of organisations (e.g. NGOs, governments and researchers). Especially for complex global supply chains where companies rely on many geographically or culturally distant suppliers, partnering with other organisations such as NGOs might be an effective approach to achieve meaningful sustainability outcomes on the ground (Koberg and Longoni, 2019).

The perception discussed in this study of the limited leverage of end-buyers in supply chains and limited capacity to engage with other stakeholders demonstrates the challenge end-buyers face in affecting meaningful change. Therefore, for some companies, it might be more effective to join industry initiatives (e.g. RSPO) to collectively have more power in the market. Industry leaders[18] and researchers (e.g. Larsen et al., 2018) have been calling for some time for importing governments to better regulate environmental and social standards in supply chains. The UK, EU and several of its member states are currently considering the implementation of due diligence laws restricting the import of commodities linked to deforestation (UK, 2020; EC, 2020b). These kinds of regulations could help ensure that it is not only leading companies who are requiring their suppliers to ensure commodities are not associated with deforestation. However, as illustrated in this study by the responses of NGOs, the traceability of imported 'embedded' commodities would need to be improved so that companies can monitor and report compliance to this law. Additionally, the European Parliament (EC, 2020c) has highlighted that this law should be extended to include carbon-dense and biodiversity-rich ecosystems to avoid conversion pressure onto these areas. To be able to implement this policy successfully, existing data providers may then need to broaden their current focus, which will likely require additional research-investment and knowledge co-production.

A lack of evidence has been mentioned as one reason for the limited implementation of approaches aiming to improve sustainability at sub-national scale (Reed et al., 2020). To identify whether and to what extent science-based evidence leads to changes in practice, monitoring of outcomes is essential (Reed et al., 2019). There is also a remaining question about who along the supply chain

[18] https://www.reuters.com/article/us-foundation-climatechange-forests/ending-deforestation-is-smart-policy-officials-idUSKCN0HI0ZD20140923

would have the burden to gather data and prove the sustainability of practices: Is it the responsibility of manufacturers, their suppliers, their sub-suppliers, governments or traders? Efforts to increase data transparency on supply chains and their impacts can help to identify responsibility of different actors and thus leverage points (e.g. actors or regions) to improve sustainability of the entire system (Rueda, Garrett and Lambin, 2017), but – from the perspective of end-buyers – it can also help to identify actors with common goals with whom to work in partnership. In this regard, research should also try to understand the motivations of actors of emerging and developing consumption markets who – along with established markets – will be critical in developing solutions to current challenges.

2.4.3 Further research on supply chain stakeholder needs

While this study offers valuable insights for academia and practice, the scope of my work leaves areas for future research to focus on. Firstly, in this study I adopted the perspective of actors distant from producing regions. Future research could extend the interview sample to include additional stakeholders linked to the value chain such as traders, investors, producers (both large and smallholder), and governments. In this study I used NGOs to represent the 'voice' of Western consumers and, to some extent, to represent the opinions of farmers 'on the ground', but future research should include those actors more representatively. Secondly, it is likely that those individuals that were willing to share their time and knowledge in my interviews were likely part of leading organisations who are already relatively well-informed, set relatively ambitious sustainability targets and are motivated to act on sustainability challenges. I chose these organisations based on their in-depth knowledge which they likely gained through years of practical experience aiming to improve the sustainability of the organisations who they work for. I believe my sample of manufacturers and retailers is representative for leading organisations as they will likely have similar information needs. However, in future, the sustainability performance expectations of end-buyers' stakeholders (e.g. investors, consumers, producing governments) will increase and therefore organisations who are not currently as interested in these concerns will likely need this kind of information in future. Stakeholder-led research to understand the needs of these non-leading end-buyers is needed. Thirdly, little is known about consumer preferences in developing and emerging markets such as India and China where demand for commodities is projected to increase in future and where the import of animal feed linked to tropical countries is rapidly increasing. My study focused on societies where the demands to improve the sustainability of food systems is currently largest, but future research should also try to understand the motivations of actors of emerging and developing consumption markets.

2.5 Conclusion

My findings reveal the complexity of sustainability challenges linked to demand for commodities in global supply chains. Consuming societies are linked through retailers and manufacturers to producing societies but also the natural environment in which the commodities are produced. Guidance towards environmentally sustainable production of commodities therefore requires careful evaluation of possible unintended consequences on other geographies and people to avoid burden shifting. The challenge is to provide guidance to navigate the complexity but avoid actors feeling overwhelmed, at the risk of subsequent in-action. More dialogue is required between actors in producing countries and those in consuming countries to negotiate common goals and align monitoring and actions. Nevertheless, as providing detailed data is costly, research needs to ensure that new data generation is focused on aspects where it can lead to better sustainability outcomes. Here, an iterative approach to co-produce knowledge together with NGOs, data providers, business representatives and other relevant stakeholders will be helpful to ensure that science supports the decisions with a sufficient amount of information to avoid unintended consequences and maximise co-benefits towards sustainability. All stakeholders involved in these complex supply chains systems should ideally be given a ‘voice’ to ensure successful implementation. Academia might also benefit from closer collaborations with ‘impact extenders’ like NGOs or thinktanks who could help them to translate science to a non-academic audience.

Chapter 3 Multi-indicator analysis

South American soy production linked to international consumption: spatially explicit footprints for land use change emissions, biodiversity, water scarcity and soil erosion

Abstract

Given its multi-functional nature, it is a challenge managing land to meet multiple goals of food provisioning, climate mitigation and biodiversity conservation. Whilst there is a lot of interest by the private and public sector (as well as tool development) related to reducing tropical deforestation, less knowledge exists, however, about the impact of commodity production on other environmental sustainability challenges in producing landscapes. Using Life Cycle Assessment principles, I estimated the water and land use and land use change impacts on greenhouse gas emissions, water scarcity, biodiversity and soil erosion embedded in soy exports from Argentina, Brazil and Paraguay. I found a large variability across sourcing regions and importing countries. Taking a 20-year land use change amortisation period, I found that the states with largest median soy-induced land use change emissions were located in the Brazilian Amazon (Para and Rondônia), the Argentinian Chaco (Salta) and some of the agricultural frontier states of Brazilian Cerrado 'MaToPiBa' (particularly Maranhao and Piaui). However, several of these states had soy-related low water scarcity (Para, Rondônia), soil erosion (Maranhao, Piaui) and biodiversity (Salta, Maranhao). These differences between soy producing states also affected which export countries had the largest footprints depending on their sourcing pattern: Brazil had the largest soil erosion and biodiversity footprint, Spain the largest LUC carbon footprint and China the largest water scarcity footprint. Additionally, for most categories, impacts were concentrated in few municipalities whereas the majority of producing regions were located in rather low-impact regions. This study illustrates that trade-offs arise (e.g. between land use change emissions and soil erosion) and that therefore efforts are needed for more strategic land use planning to manage co-benefits across multiple sustainable development goals. Additionally, given the large variability, traceability in supply chains should be encouraged at least until municipality scale for large countries like Brazil to identify the impact hotspots and actors linked to those. This study also indicated that there should

be more efforts to harmonize data and indicators to account for spatial variability of land use and land use change impacts so that progress towards targets of different actors can be more easily reported and compared.

3.1 Introduction

Global trade is making it challenging to understand how the demand on food, feed and fuel is leading to distant environmental impacts (Liu et al., 2013). In particular, trade in agricultural commodities has doubled in the last 15 years (OECD, 2020) shifting the environmental burden to selected producing countries. Trade and consumption of agricultural commodities is driving 26 % of deforestation in tropical and subtropical forests (Pendrill et al. 2019a), making it the second largest source of greenhouse gas emissions (Smith et al., 2014) and a major driver of biodiversity loss (Symes et al., 2018). Therefore, within the New York Declaration on Forests, more than 60 nations and 59 private companies in 2014 committed to eliminate deforestation driven by commodity consumption by 2030 (UN, 2019). The European Green Deal includes the 'Farm-to-Fork' (F2F) Strategy published in May 2020 which is aligned to the Sustainable Development Goals (SDGs) and aims to reduce the EU's environmental and climate footprint, protect natural resources such as water and soils and reverse biodiversity loss along the entire supply chain from agricultural production to consumption (EC, 2020d). Trade is considered part of the EU's ambition to lead the global transitions towards climate neutrality and a sustainable and resilient food system (EC, 2021a). The environment ministers of the G7 encourage solutions which can "contribute to multiple SDGs simultaneously and achieve mutually beneficial outcomes" aligned to the 2030 Agenda for Sustainable Development (IISD, 2019). In the implementation of the 2030 agenda, interactions between different targets emerged as an issue and must be considered to make policies and planning effective (Weitz et al., 2018). Therefore, practical tools for footprinting are needed to understand the impacts of trade in producing countries and to monitor progress of individual governments and businesses towards their goals to reduce greenhouse gas emissions, biodiversity loss and protect natural resources such as water and soils.

Soy is the world's most internationally traded agricultural commodity due to their use in animal-feed (COMTRADE, 2020) but also other uses such as cooking oil and biofuel production (Castanheira and Freire, 2013). From 2000 to 2020, the international trade in soy quadrupled (FAOSTAT, 2021), driven by the increasing demand for animal products in China and other developing markets. This increase in soy export largely came from Brazil (700 %), Paraguay (200 %), USA (130 %) and Argentina (100 %) which are all among the five largest global soy producers (FAOSTAT, 2021). This acceleration in production lead to soy becoming one of the key commodities driving most deforestation and natural vegetation loss globally (Pendrill et al. 2019b). As a response to the growing concern by consumers, governments, traders and multi-national companies (Nepstad et al., 2014); several supply chain policies were established aiming to reduce detrimental environmental impacts of soy expansion. Examples of initiatives which reduced land conversion are the Soy Moratorium in 2006 in the Brazilian Amazon (Nepstad et al., 2014) and a federal forest law established in 2007 in Argentina which at least in some provinces reduced conversion (Nolte et al., 2017). However, efforts to reduce deforestation rates in the Amazon lead to increased land conversion in the neighboring savannah-biome Cerrado (Rausch et al., 2019). Therefore, it is expected that actors might shift their sourcing away from 'hotpots' of environmental destruction to alternative producing regions with less detrimental effects (Meyfroidt et al., 2018). Recently, a lot of research has focused on soy-induced deforestation in the Cerrado 'MaToPiBa' region (Brazilian states of Maranhao, Tocantins, Piaui and Bahia) (e.g. Escobar et al., 2020; Green et al., 2019; Zu Ermgassen et al., 2020a).

One of the barriers to robust environmental footprints is a lack of traceability and transparency of global supply chains to account for the spatial heterogeneity in producing regions (Garrett et al., 2019; Lambin et al., 2018; Godar et al., 2015). Most studies on the impact of global agricultural trade on land systems rely on national-level data for trade flows and associated environmental impacts (Kastner et al., 2021). Increasingly, indicators are being developed to allow fine-scale assessments such as for carbon emissions (Escobar et al., 2020), biodiversity (Chaudhary and Brooks, 2018) and water scarcity (Boulay et al., 2018). However, as the sub-national origin of agricultural commodities with complex supply chains (e.g. soybeans, palm oil, meat) is often unknown, in practice it is challenging to estimate potential impacts associated with their production which requires detailed information on the agricultural production origin (Godar and Gardner, 2019). To overcome this limitation, data on the transparency of supply chains can be used to account for the sub-national sourcing pattern affecting environmental impacts, as illustrated within Lathuillière et al (2021). An important decision-support tool in this context is Life Cycle Assessment (LCA) which quantifies environmental impacts across all stages of a product's (often globally distributed) life cycle from resource extraction or crop cultivation until disposal. Within a LCA there are four main steps: (1) goal and scope definition, (2) life cycle inventory (LCI), (3) Life Cycle Impact assessment (LCIA) and (4) normalization and interpretation.

Data availability often limits the accuracy of the LCA inventory (i.e. gathering inputs and outputs of each process in the life cycle) and the impact assessment stage (i.e. characterizing the impact of the inputs and outputs based on their environmental pathway). As a result of this, LCAs are often limited in regional detail or context-dependent (Hellweg and Milà I Canals, 2014) increasing the spatial uncertainty and therefore limiting their relevance (Patouillard et al., 2019). To overcome this limitation, LCA approaches are emerging that try to represent detail in both the heterogeneity in supply chains as well as variability in environmental characteristics in producing regions (Lathuillière et al., 2021; Escobar et al., 2020). These studies use data-driven sub-national trade flow mapping data for regionalisation (e.g. Smith et al., 2017). However, there are a lack of studies consistently covering more than a single country and/or multiple biomes (Gardner et al., 2019). Existing research often focuses on a single country such as Brazil (Lathuillière et al., 2021; Escobar et al., 2020) or a few biomes such as tropical forests (e.g. Amazon, Chaco) and savannahs such as the Cerrado (Green et al. 2019). There are few studies considering the impacts of soy expansion in other biomes or across different producing countries (Jia et al., 2020). Additionally there are a lack of studies assessing impacts across multiple environmental concerns to allow the identification of environmental trade-offs and/or potential synergies. A better understanding of the links between commodity trade and environmental impacts such as deforestation could help guide efforts towards more sustainable production and consumption as highlighted in the Sustainable Development Goals, which aim to eliminate deforestation by 2030. As global actors (e.g. multi-national companies) and large consuming countries have widely distributed supply chains, analysis is needed that is consistently applicable across multiple producing countries, and even across the entire world (see Chapter 2).

To overcome the fact that many LCAs are limited in their geographic scope, here I combine recently developed high-resolution land cover maps from the European Space Agency Climate Change Initiative (ESA CCI), globally consistently available indicators (Sonderegger and Pfister, 2021; Boulay et al., 2018; Chaudhary and Kastner, 2016), soybean harvested-area maps (Song et al., 2021) and sub-national supply chain mapping data from Trase.earth. ESA CCI land cover maps consistently cover three important globally-significant soybean producing countries associated with current land conversion (i.e. Brazil, Paraguay and Argentina) over long time periods (1995-2019). Therefore, these maps allow the study of land conversion across a wide range of land cover types (e.g. shrubland, grassland, mosaics of natural land), across a time period of two decades and across multiple producing regions.

In this study I aim to answer the following three questions to generate better knowledge on how to better manage environmental impacts linked to demand for agricultural commodities.

(1) *How do land use and land use change-related impacts from soybean production differ between biomes and jurisdictions when applying a consistent approach across three major South American countries?*

While many sub-national studies exist focusing on a single country (often Brazil) or a single environmental impact, I use globally available data and Characterization Factors (CFs) for a consistent approach to compare multiple possible soy sourcing regions.

(2) *How do consuming soybean countries differ in land use and land use change impacts when combining physical flow accounting data with traditional LCA?*

This approach allows for balancing of scale with detail by accounting for the heterogeneity of environmental impacts in producing regions linked to consuming countries (Escobar et al. 2020).

(3) *Based on the sub-national variability of different environmental impacts: What is the appropriate spatial (and temporal) resolution of data to identify geographic hotspots and maximise co-benefits to guide decision-making in government and industry?*

The latter was mentioned as an un-answered question by Hellweg and Milà I Canals (2014) and Mutel, Pfister and Hellweg (2012).

3.2 Materials and methods

In this study, I used a hybrid approach similar to Escobar et al. (2020)[19] to estimate LUC emissions, biodiversity loss, water scarcity and soil erosion embedded in the production of agricultural commodities by combining LCA principles with the physical trade flow model 'Spatially Explicit Information on Production to Consumption Systems' (SEI-PCS). With this approach I capture the spatial variability in land use change, yield and resulting Characterization Factors (CF) across soybean producing regions in Brazil, Argentina and Paraguay. Within LCA, impacts are estimated based on the inventory component affected by agricultural management practices (green boxes in Figure 3.1) and the impact assessment component affected by regional environmental characteristics determining susceptibility to impacts (e.g. local water scarcity, biodiversity or carbon storage in natural vegetation), and related CFs (red boxes in Figure 3.1).

[19] Escobar et al. (2020) only estimate impacts on Greenhouse Gas emissions but no other impact categories

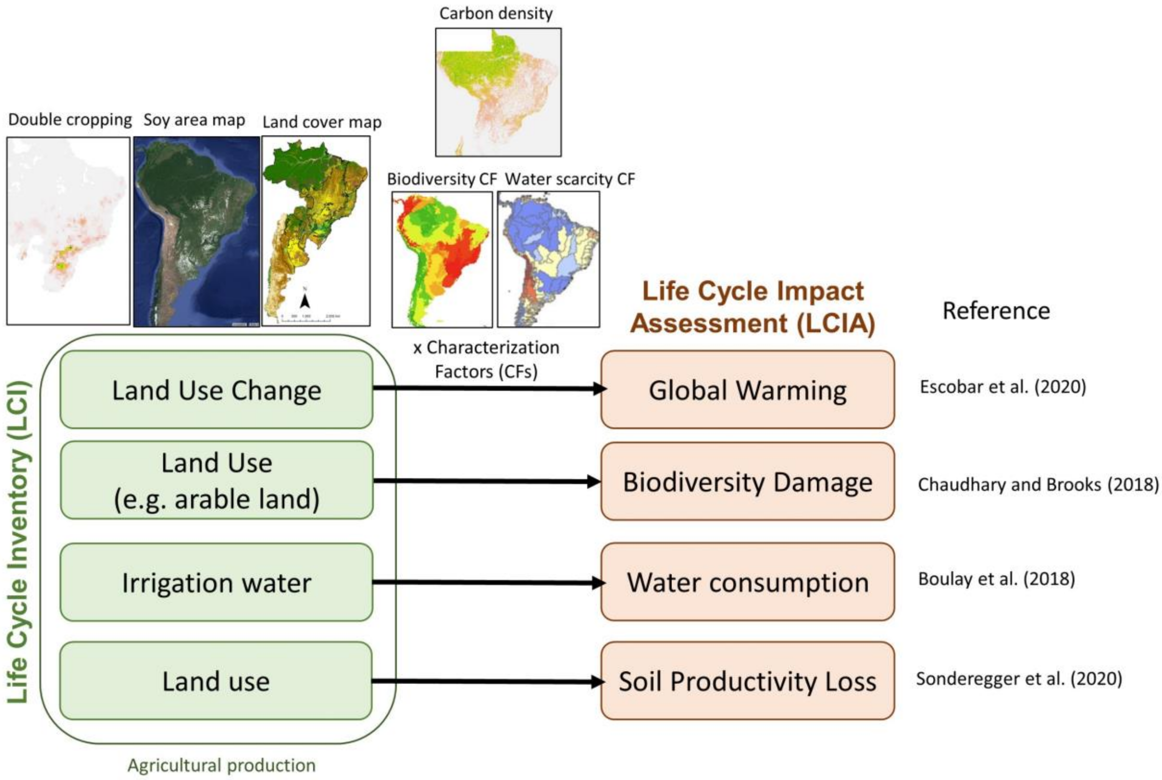

Figure 3.1. Life Cycle Inventory and Life Cycle Impact Assessment of the agricultural stage of soybean production. Argentina, Brazil and Paraguay (source: Santoro et al., 2021; Song et al., 2021; Boulay et al., 2018; Chaudhary and Brooks, 2018; ESA CCI, 2017)

3.2.1 Goal and scope

The functional unit (FU) of the study was "one tonne of soybean equivalents" (soy-eq.) leaving the farm-gate, i.e. transportation and processing of soybeans was excluded. One soy-eq. is defined as the amount of raw soybean embedded in flows of oil, cake or beans being exported (Godar et al., 2015). This allows comparison across different soybean products exported. Therefore, the system boundary includes the life cycle sub-stages of agricultural production and land use change. I compared one tonne of soybeans produced in Brazil, Argentina and Paraguay and exported to the fifteen largest consumers of these countries in 2017. The results are therefore expressed in an impact score per soy-eq.

Land use impacts were ascribed to the producing region in which the crop was most likely cultivated as identified using 30-metre soybean harvested area maps from 2017 (Song et al., 2021). These impacts were then ascribed to the most likely consuming country. I used regional data from the Trase project including export volumes of soybean and derived by-products from Brazilian municipalities, departments in Argentina and districts in Paraguay (herein referred to as municipalities for ease of reference) to related countries of import in 2017. These were aggregated to states in Brazil, provinces in Argentina and departments in Paraguay (herein referred to as states). This approach allows the estimation of environmental impacts associated with each soybean exporting jurisdiction as well as consuming country, depending on the relative export volumes. The latter is referred to as 'Commodity Supply Mix' and was developed by Lathuilliere et al. (2021). The resulting supply chain maps can be downloaded from Trase and I used the latest versions available (referred to as Trase SEI PCS version v2.5.0 (Brazil), v1.2.1 (Paraguay) and v1.0.1 (Argentina)). From the producing side, I estimated environmental impacts at municipalities, state, biome and country level. This resulted in the estimation of environmental impacts embedded in soybean exports of 2275 municipalities in Brazil, 207 in Argentina and 182 in Paraguay. From the consuming nation perspective, environmental impacts are calculated for the fifteen largest consumer countries based on the production origin of each countries' soybean imports within the three studied producing countries. Concerning trade flows for which the municipalities were unknown, I assumed country average environmental impacts, which I weighted by each municipalities' soy production in 2017.

3.2.2 Life Cycle Inventory

The LCI relied on Trase's SEI-PCS annual sub-national production and harvested area data to estimate soybean land occupation area for each studied producing country (Trase, 2018). Consequently, land occupation (hectare-year) per tonne soybean is estimated as the inverse of the yield (tonne per hectare).

Land use change

Land use change emissions from cropland expansion attributed to producing municipalities and biomes included changes in the carbon stocks of aboveground- and belowground biomass and soil organic carbon. These emissions (in t CO_2 eq $ha^{-1} yr^{-1}$) were amortized over a 20-year time period to annualize the emissions after the conversion to cropland, following the PAS2050-1 methodology (BSI PAS, 2012). For cropland areas where conversion from natural land took place more than 20 years ago, no emissions from land use change were attributed. See Lam et al. (2021) for a detailed description of the methodology to calculate greenhouse gas emission following land conversion (see section S.2.2 Carbon stocks estimation).

To allow a consistent comparison of land cover change across the three producing countries in South America, I chose the land cover maps of ESA CCI (2017). This dataset has global coverage with a high spatial resolution (300 x 300 m), provides yearly land cover maps between 1992 and 2019 and includes 23 different land cover classes (see Table S 2.1). They have been used previously to analyse cropland expansion at the global level by Eigenbrod et al. (2020) and Lam et al. (2021). 20-year historical soy-induced cropland expansion was identified at the polygon-level by intersecting raster maps of soybean harvested area by Song et al. (2021) with ESA raster maps in 1996 across soy producing municipalities and biomes in Argentina, Brazil and Paraguay (see Table S 2.1 for an overview of ESA CCI land cover classes). Land use change was calculated for the current major producing soybean biomes and municipalities (see Figure 3.2). Following Eigenbrod et al. (2020), I excluded the ESA CCI land cover classes 'Mosaic of agriculture' (30 and 40) from the attribution of land use change to soybean production, as this land cover type is likely smallholder agriculture (Eigenbrod et al., 2020). I therefore assumed that conversion of 'Mosaic of Agriculture' to soy is rather an intensification of agriculture rather than natural land conversion (see next chapter for an analyses of the sensitivity to this choice). I assumed a one year lag period between land use change and soy production, following Escobar et al. (2020) and TRASE (2020). Therefore, the land use change since 1996 was attributed to soybean production in 2017.

Aboveground carbon (AGC) stocks for the different land cover types were derived from a combination of different data sources. For the forest land cover class, I used the raster data of global forest aboveground biomass (AGB) from Santoro et al. (2021) using mean values for each municipality (excluding values of 0) (see **Figure S 2.1** for a comparison of each biome's mean, maximum and 90th quantile). As in Lam et al. (2021), the Santoro dataset was selected for forests as it provides globally consistent AGB values of both tropical and non-tropical forests at a high spatial resolution (100 x 100 m). The Baccini et al. (2012) forest carbon dataset used in Escobar et al. (2020) was not deemed suitable for this study as it only covers tropical forests therefore not providing AGC estimates for southern Brazil and Argentina (though it covered Paraguay). To convert aboveground biomass from Santoro et al. (2021) into carbon, I used the conversion value of 0.47 tonne AGC per tonne AGB provided by Ruesch and Gibbs (2008). For the other non-forest land cover classes I used the Intergovernmental Panel on Climate Change (IPCC) default Tier 1 aboveground and belowground carbon stock values provided by Ruesch and Gibbs (2008) which are available for each carbon zone of the world (see Table S 2.2).

According to Spawn et al. (2020), the maps provided by Ruesch and Gibbs (2008) still remain the main source of global above- and belowground carbon estimates going beyond a single land cover type. Average estimates of carbon stocks were, for each land cover class (ESA, 2017) in each municipality, derived by intersecting the carbon zone polygons from Ruesch and Gibbs (2008) with the municipality's polygons. Belowground carbon stocks were estimated as a share of aboveground carbon using root-to-shoot ratios for each land cover type within each carbon zone provided by Ruesch and Gibbs (2008). After conversion to cropland the aboveground- and belowground carbon stocks were assigned a value of zero as soybeans are annual crops where all biomass is taken off the field after harvest (Escobar et al., 2020). To calculate emissions from soil carbon stocks, I followed the approach of Escobar et al. (2020). To estimate soil organic carbon (SOC), I used a raster dataset (5 x 5 km) covering South America from Guevera et al. (2019) and soybean-specific land management factors to estimate soil organic carbon loss following the conversion of natural land to soybean cultivation (Esteves et al., 2016). Overall, the losses of carbon stocks were expressed in CO_2 eq. emissions and aggregated to biome level and municipalities to be able to link them to Trase supply chain data.

Double cropped areas were derived from national production statistics from Brazil (IBGE, 2018), Paraguay (INBIO, 2017) and Argentina (Ministry of Agriculture, 2017) (see maps in **Figure S 2.2**) and used to allocate land use associated impacts to the second (or third) crop. I assumed that the second (or third) crop would be responsible for half (or a third) of the land use-associated impacts per unit area, following Escobar et al. (2020). Therefore, whether crops are produced in double or triple-cropping cycles has a large effect on the estimated environmental impacts.

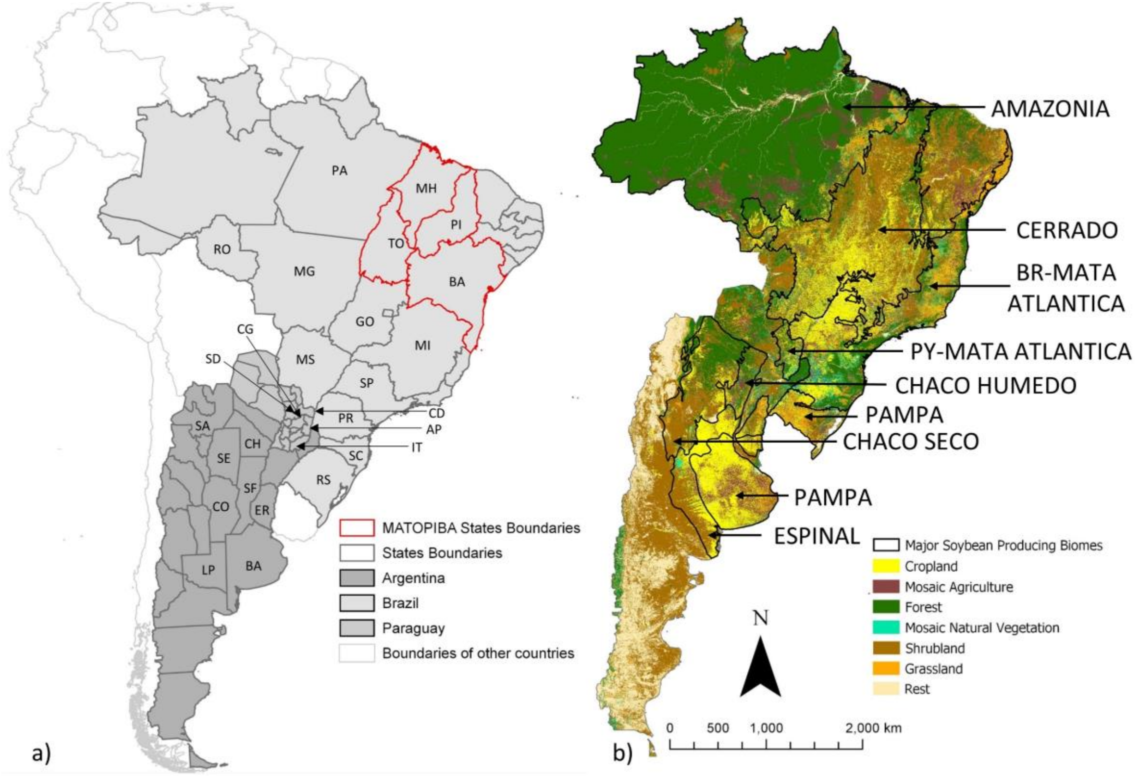

Figure 3.2. Map of the study area with borders of major soybean producing states a) and land cover of major soybean-producing biomes b) in Brazil (BR), Argentina (AR) and Paraguay (PY) (adapted from (ESA CCI, 2017). ESA CCI Land Cover Classes were aggregated to land cover classes used in this study. State names were abbreviated with AP = Alto Parana, BA = Bahia, BA = Buenos Aires, CD = Canindeyú, CG = Caaguazú, CH = Chaco, CO = Cordoba, CZ = Caazapá, ER = Entre Rios, GO = Goias, LP = La Pampa, MG = Mato Grosso, MH = Maranhao, MI = Minas Gerais, MS = Mato Grosso do Sul, Para = PA, PI = Piaui, PR = Parana, RO = Rondônia, RS = Rio Grande do Sul, SA = Salta, San Pedro = SD, SC = Santa Catarina, SE = Santiago del Estero, SF = Santa Fe, SP = Sao Paulo, TO = Tocantins.

Water

As no spatially-explicit irrigation data were readily available, I used as inventory data for Argentina a value of 170 m^3/ton soy and for Brazil and Paraguay 140 m^3/ton soy based on Caldeira et al (2018). These numbers are in line with estimates that currently 2-4 % of soybeans grown are irrigated in those three countries (www.yielgap.org) requiring around 6000 m^3/ton if 100 % of soybean harvested area is irrigated (Flach et al., 2016).

3.2.3 Life Cycle Impact Assessment

I assessed footprints covering potential impacts on natural resources (soil, water) as well as the natural environment (biodiversity, greenhouse gas emissions) within an LCA framework (Figure 3.1). These impact categories were chosen because they were identified as key priorities in the preceding stakeholder engagement process (see Chapter 2), but also as their CFs were available at the high spatial resolution which was required to study the benefit of spatially refined agricultural trade flow data in LCA. Additionally, for these impact categories the required inventory data are available across the entire world, allowing the potential for a consistent approach for consuming countries with global sourcing patterns. As common in LCA, land use footprints are calculated by multiplying flows of land occupation (i.e. land use) and land transformation (i.e. land use change) by CFs describing the change in quality of this land due to the human use (e.g. Ridoutt and Navarro Garcia, 2020).

3.2.3.1 Land use change emissions

The climate change potential is expressed in CO_2-eq in terms of the additional warming over the next 100 years as common practice in LCA. The PAS2050 method (BSI PAS, 2012) was followed to calculate CO_2 emissions from land use change.

3.2.3.2 Biodiversity

Potential impacts on biodiversity were calculated using the CFs developed by Chaudhary and Brooks (2018). These CFs represent the latest evolution of models which came out of a consensus-finding process of experts lead by the Life Cycle Initiative of the UN Environment Program (UNEP) and originally developed by Chaudhary et al. (2015). These CFs are based on the countryside Species Area Relationship (cSAR) model describing the relationship between available habitat area and the number of species (see **Figure S 2.3** for CFs of each ecoregion). Therefore, this indicator describes the potential species extinctions arising due to human land occupation. The assumption is that the more natural land (i.e. habitat) that has already been converted historically within a biome, the more likely that species will go extinct (Chaudhary et al., 2015). CFs are available for five different human land use types and three different land use intensities (i.e. minimal, light and intensive). I applied the CFs provided for intensive crops as I assumed that the majority of soybeans for export are produced intensively. I have calculated biodiversity impacts from land occupation (see section S.2.5 Calculation of Biodiversity Damage Potential for detailed equations).

I used the ecoregion-specific CFs for occupation which are expressed as Potentially Disappeared Fraction (PDF) of Species Loss per m^2 land occupation (Chaudhary and Brooks, 2018) and based on the ecoregion maps provided by The Nature Conservancy (TNC, 2019). Chaudhary and Brooks

(2018) provide CFs separately for mammals, birds, amphibians, reptiles and plants though for completeness I have used the CFs aggregated across all taxa, as recommended by the Life Cycle Initiative of UNEP SETAC (Society of Environmental Toxicology and Chemistry). To aggregate the CFs to the municipalities, I area-weighted the ecoregion-specific CFs by the share of soybean area in each ecoregion within each municipality. The occupation impact (OI) can be calculated as the product of the Characterization Factor for Occupation (CF_{Occ},) the occupied area A_{Occ}, and the duration of the occupation process t_{Occ} (Koellner et al., 2013) for each land use$_i$ and administrative level region$_j$.

$$\boldsymbol{OI_{LU_{i,j}}} = \sum_i \boldsymbol{CSM_i^j}\left(\boldsymbol{A_{Occ_{i,j}}} \times \boldsymbol{t_{Occ\,i,j}}\right) \times \boldsymbol{CF_{Occ,LU_{i,j}}} \quad \text{(Equation 1)}$$

$$\boldsymbol{CSM_i^j} = \frac{\boldsymbol{S_i^j}}{\sum^i \boldsymbol{S_i^j}} \quad \text{(Equation 2)}$$

Where CSM is the harvested area-weighted share of ecoregion within each producing municipality's region $_j$ following Lathuillière et al. (2021).

3.2.3.3 Water Scarcity

Within LCA, potential impacts resulting from water consumption are estimated using a water scarcity indicator. The water scarcity indicator Available Water Remaining (AWARE) resulted from a consensus-finding process of water experts lead by the Life Cycle Initative of UNEP SETAC and can be found in Boulay et al. (2018). This indicator describes the potential to deprive other users of water (human or environment) downstream. The assumption is that the less water is available in the watershed, the more likely the water consumption will lead to a deprivation of another user (Boulay et al., 2018). The indicator is expressed in world equivalent m^3 to allow comparison of the same product across different regions and ranges between 0.1 and 100. Spatially-explicit indicators are available for each watershed of the world. This means that the CF describing the water scarcity is the same for any region within the watershed (see map in **Figure S 2.4**). I used the annual aggregated CFs for agricultural use (Boulay et al., 2018). It has to be noted that AWARE only ascribes potential impacts to blue water consumption (i.e. irrigation) but not to green (i.e. rainwater) water consumption. However, I do not expect this to substantially influence the relative ranking between producing regions (also see discussion). Soy-production related water scarcity footprints were calculated by area-weighting water scarcity by intersecting maps of water scarcity (Boulay et al., 2018) with the soybean harvested area from Song et al. (2021). To aggregate the CFs to the municipalities, Equation 1 and 2 were followed.

3.2.3.4 Soil productivity loss

Impacts on soil were estimated by using CFs for water erosion developed within an LCA framework by Sonderegger et al. (2020). Sonderegger et al (2021) developed CFs for soil erosion based on the Revised Universal Soil Loss Equation (RUSLE) describing soil erosion depending on erodibility (soil texture; K); erosivity (rainfall-runoff; R), slope length and steepness (topography; LS) and crop practice factor (tillage; CP). CFs for the RUSLE component which cannot be influenced by agricultural management (i.e. KRLS) were provided as a raster file by Sonderegger et al. (2020), whereas the crop management factor was extracted from the literature (see Figure 3.1). Due to a lack of better knowledge, I assumed a worst-case assumption of 100 % conventional tillage practices (i.e. ploughing) which is typical for South American soybean production (Escobar et al., 2020). Therefore, I used the related crop management practice factor of 0.1576[20] found in an empirical study in Brazil for a soybean-wheat crop rotation (Da Silva et al., 2020). Water erosion CF are expressed in the unit % productivity loss per soy eq. tonne over the next 50 years (Sonderegger et al. 2020). Sonderegger et al. (2020) derived the erosion CFs by multiplying the soil erosion rates (from the RUSLE model) with a crop-specific conversion factor translating soil erosion rates into yield losses.

The soil-dependent CFs are available aggregated to country and sub-national level but also as raster files (1 km resolution). I have used the CFs aggregated from the raster maps to municipalities. I took the crop-specific and continent-specific conversion factor converting erosion rates to productivity loss (unit in %/Mg) from Sonderegger et al. (2021).

In cases where the sub-national origin was 'unknown' in the TRASE data, I assumed national-average impacts weighted by the fraction of the commodity trade volume produced in each municipality (following Lathuillière et al., 2021).

Overlaying rasters of soybean harvested area with land cover maps to analyse direct soy-induced land use change was conducted with code developed in Google Earth Engine. The output of Google Earth Engine was a .csv file of the area converted of each ESA CCI (2017) land cover class to soybean within each municipality and biome. The data in the .csv file was further analysed within the

[20] Reduced tillage practices would lower the crop management factor to 0.0407 and no-tillage to 0.0368 (Da Silva et al. 2020).

software R. The rest of the analyses and graphs were performed in R statistical software (v4.0.4; R Core Team, 2021) in Rstudio (v1.4.1006; R Studio Team, 2021), with *tidyverse, dplyr, ggplot2, tiff, sp, rgeos, exactextractr, raster, ncdf4, sf, RcolorBrewer* packages.

3.3 Results

3.3.1 Biome-level comparison

3.3.1.1 Greenhouse Gas emissions from direct land use change

The area and type of land cover converted to soybean production in the last two decades varies between biomes in Brazil, Argentina and Paraguay. I estimated how much of the soybean harvested area in 2017 had been natural land twenty years ago. Most natural land was converted per tonne soy-eq. in the Brazilian Amazon (98 m^2/t soy-eq), followed by the Argentinian Chaco Seco (Spanish: Dry Chaco) (54 m^2/t soy-eq) and the Argentinian Chaco Humedo (Spanish: Moist Chaco) (51 m^2/t soy-eq) (Figure 3.3a). In contrast, least land was converted in Argentina in the Pampa (9 m^2/t soy-eq) and the Espinal (11 m^2/t soy-eq). Differences between biomes become even more pronounced when this land conversion is translated into greenhouse gas emissions: the Amazon has 28 times more greenhouse gas emissions from land conversion than the Argentinian Pampa per ton soy-eq. (Figure 3.3b). This is due to the higher share of carbon-dense forests being converted in the Amazon (88 %) compared to the Pampa in Argentina (17 %); largely a result of the different natural vegetation types in these biomes (see land cover map in Figure 3.2). Land use change emissions are lower in the Mata Atlantica in Brazil and the Pampas in Argentina and Brazil. In those biomes natural land was converted to agriculture more than 20 years ago as they are geographically closer to coastal ports and domestic consumption centres such as Sao Paulo and Rio de Janeiro. However, as land use change related impacts are only allocated if they happened in the 20 years before crop production, these historical emissions are not allocated. As the tropical moist forests in the Amazon store more carbon than the dry forests of the Chaco, the differences between these forest-biomes become more pronounced when translated from converted area to carbon emissions.

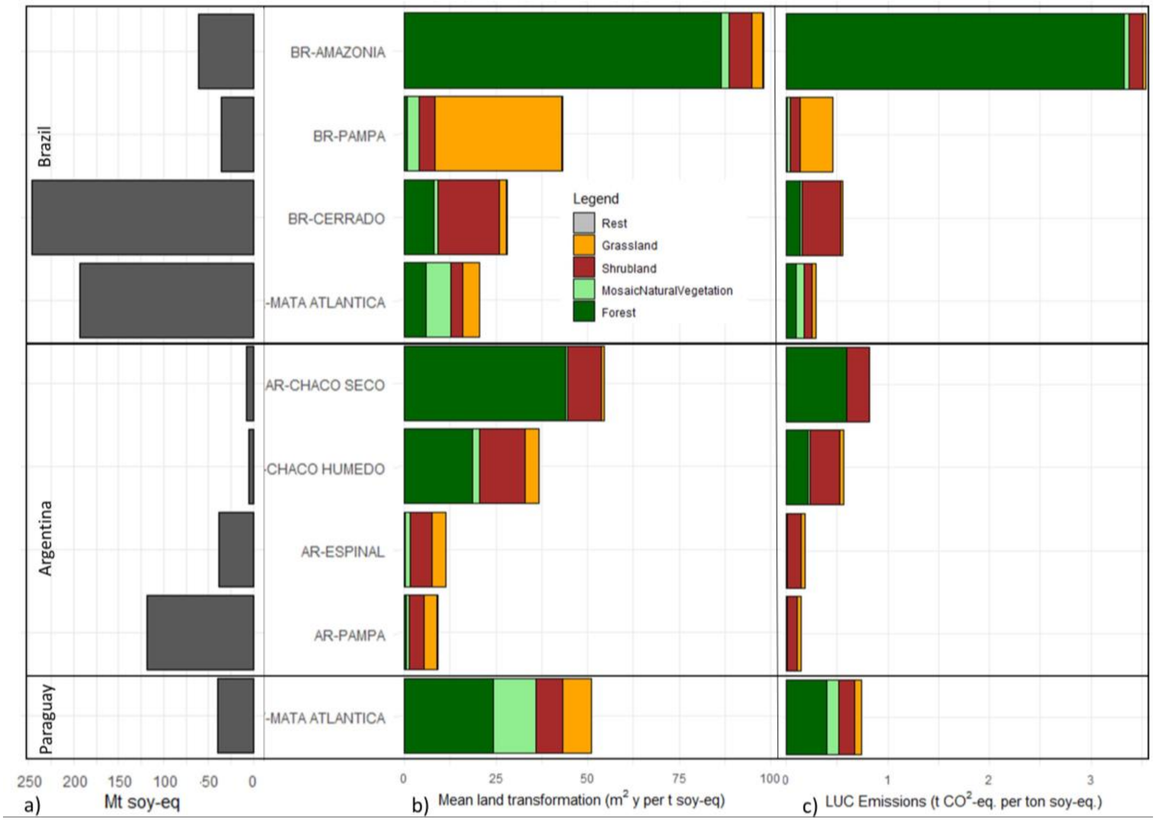

Figure 3.3. For each major soybean biome, soybean production volumes (a), direct land use between 1996 and 2016 in area per soy-eq (m^2 t^{-1}) (b) and resulting emissions, as CO_2 per soy-eq. (t t^{-1}) (c). Ordered within each producing country by decreasing land conversion area.

3.3.1.2 Biodiversity

Differences between biomes in the biodiversity damage potential (Figure 3.3b) are larger than differences in land occupation (Figure 3.4). Across the biomes, land occupation LCI varied between the Chaco Humedo in Argentina with a median of 2356 m^2/t soy-eq (2255 m^2 /t soy-eq – 2998 m^2/t soy-eq) to the Pampa in Brazil with 3333 m^2/t soy-eq (3037 m^2/t soy-eq – 3703 m^2/t soy-eq) (ranges represent the variability between municipality jurisdictions expressed in first and third quartile) (Figure 3.4a). Land occupation values are also relatively small in the Cerrado in Brazil, the biome producing most soybeans in South America with 2942 m^2/t soy-eq (2559 m^2/t soy-eq -3041 m^2/t soy-eq). These ranges in land occupation are largely due to spatial differences in soybean yields. Differences between the biomes become more pronounced when considering the occupation impact (OI): the OI of the Mata Atlantica in Paraguay (11.4 x 10^{-10}/soy-eq) is more than five times higher than the OI in the Argentinian Pampa (2.2 x 10^{-10} /soy-eq; Figure 3.4b). The largest Ois are associated with biomes which either have many endemic species and/or have been subject to large-scale agricultural land conversion leaving little habit left for species (e.g. Mata Atlantica in Argentina and Brazil, see CF in Figure S 2.3).

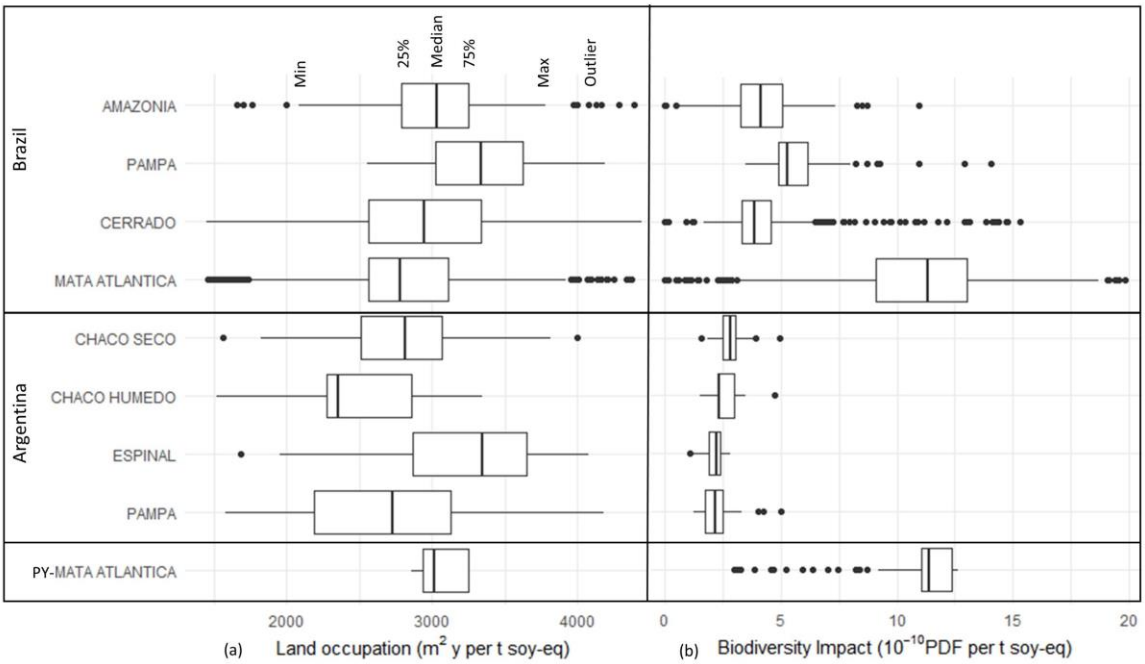

Figure 3.4. Box-and Whisker Plot of land occupation (a) and Occupation impact (b) in Global species eq. lost of major soybean producing biomes in Argentina, Brazil and Paraguay (PY) 2017 per soy-eq. Biomes are ordered within each producing country by decreasing land conversion area. (Land occupation variability of Admin-level 2 within each biome)

3.3.2 State- and municipality-level comparison

To be able to compare results across the different environmental impact categories, I calculated impacts for each major state.

3.3.2.1 Water scarcity

CFs of water scarcity at the level of municipalities range between 0.1 and 70 m^3/soy-eq. (0.93 ± 1.79; Figure 3.5). CFs between the 10^{th} and 90^{th} percentiles range between 0.52 and 1.50 indicating that the large majority of soy production is in water-abundant watersheds. The largest CFs are in the Argentinian States of San Luis and Buenos Aires and in the Brazilian states of Maranhao and Minas Gerais. More than 70 % of municipalities above the 90 % percentile are located in these four State regions. While none of these water-scarce regions in Brazil are producing large volumes of soybeans, in Argentina Buenos Aires is the largest soybean producing province (see Figure 3.5). In comparison, the water-abundant municipalities below the 10^{th} percentile are spread out over many different municipalities: in Paraguay Paraguarí, in Argentina Entre Rios and Santa Fe and in Brazil Santa Catarina and Mato Grosso. However, the variability within state can be large which is the case for the state of Maranhao in the north-east of Brazil where water scarcity varies across municipalities between 100 and more than 900 world eq. m3 per ton soy (see Figure S 2.4).

3.3.2.2 Soil Productivity Loss

Characterization factors of soil productivity loss from water erosion range between 0.2 and 9.8 % ha-yr/t soy-eq. productivity loss over the next 50 years (0.34 ± 0.47) of municipalities (Figure 3.5), illustrating the spatial variability in soil erosion between producing regions. CFs between the 10^{th} and 90^{th} percentiles range between 3.0 and 35.5 % ha-yr/t soy-eq showing also a large variability. The largest CFs are found in the southern Brazilian states of Santa Catarina, Rio Grande do Sul and Parana (see map in Figure 3.2) characterized by relatively higher precipitation. Within these three states, 88 % of municipalities with CFs above the 90^{th} percentile are found. In contrast, CFs below the 10^{th} percentile are found mostly in Argentina (69 %). In particular in the states of Buenos Aires, Santa Fe and Santiago del Estero, where rainfall events are less pronounced leading to lower erosivity.

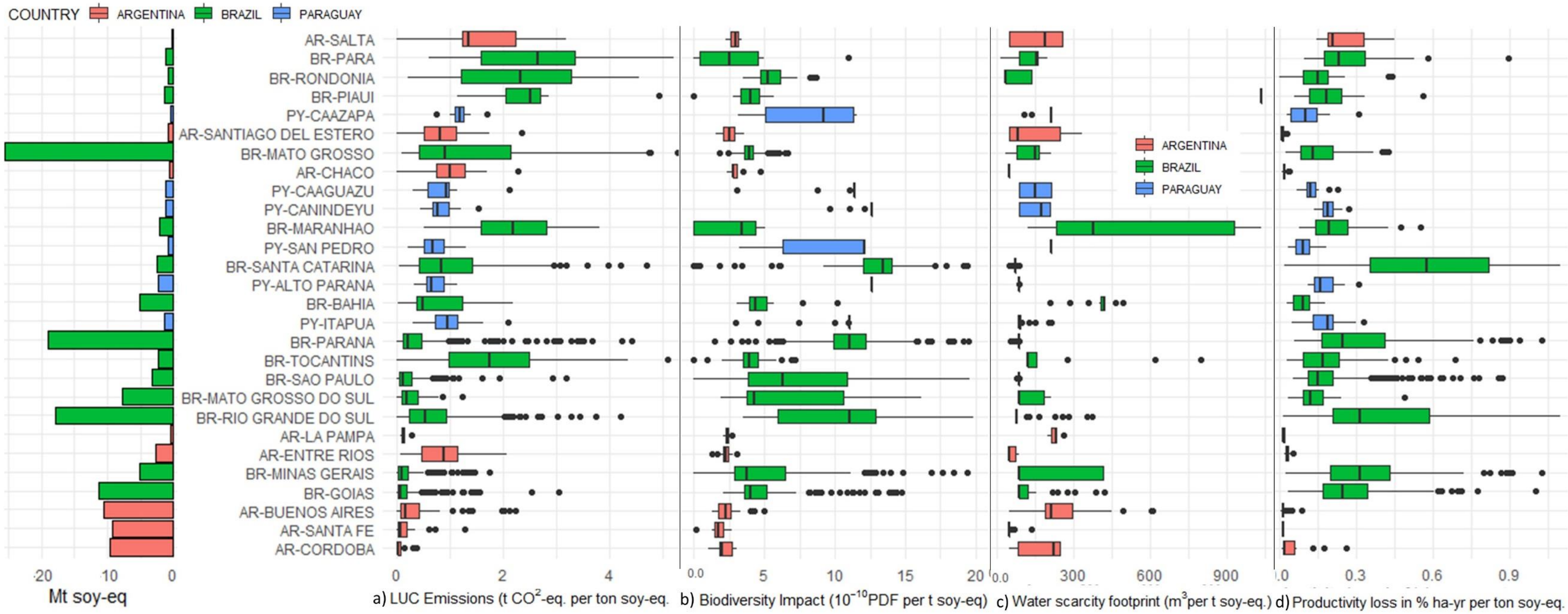

Figure 3.5. Soybean production quantity in 2017 on the left and on the right box and whisker plot of CO_2 emissions from land conversion (a), biodiversity damage (b), water scarcity (c) and soil productivity loss as % ha-yr per soy-eq due to water erosion (d) for each major state. States are ordered by decreasing deforestation area embodied in soybeans. (Calculated by weighting with the commodity mix)

Aggregating impacts from municipality to state using the commodity mix (see section 3.2.3.2 and Equation 2) identifies slightly different regions as geographic hotspots (Table S 2.5). Taking the latter approach, among the five states with largest impacts were three in the Brazilian biome Amazon (Para with 3.53 t CO_2-eq./t soy-eq), Rondônia with 2.58 t CO_2-eq./t soy-eq and Mato Grosso with 1.78 t CO_2-eq./t soy-eq.), one in the Argentinian biome Chaco (Salta 1.81 t CO_2-eq./t soy-eq.) and one in the Brazilian biome Cerrado in the 'MaToPiBa' region (Piaui with 2.07 t CO_2-eq./t soy-eq). However, most of these regions with high LUC emissions per production unit produce rather small volumes of soybeans except Mato Grosso (Figure 3.5). Those regions with large soy production had rather small LUC emissions, such as Rio Grande Do Sul (0.37 t CO_2-eq./t soy-eq.), Parana (0.34 t CO_2-eq./t soy-eq.), Goias (0.11 t CO_2-eq./t soy-eq.) and Mato Grosso do Sul (0.32 t CO_2-eq./t soy-eq.). However, many states which had low median LUC emissions (below 1 CO_2-eq./t soy-eq.) were high from a biodiversity impact perspective (Figure 3.5b) and tended to have larger soil erosion impacts of more than 0.2 % productivity loss per tonne soy-eq. (Figure 3.5d).

Estimating state-level impacts by averaging across municipalities (rather than by weighting by the commodity mix; see Equation 1 and 2 in section 3.2.3.2), increases LUC emissions especially for the MaToPiBa regions Piaui (2.51 t CO_2-eq./t soy-eq), Maranhao (2.81 t CO_2-eq./t soy-eq and Tocantins (1.81 t CO_2-eq./t soy-eq), whereas for Mato Grosso LUC emissions were lower with 1.12 t CO_2-eq./t soy-eq (Table S 2.5).

The two producing regions showing the smallest LUC emissions were Santa Fe (0.06 CO_2-eq./t soy-eq.) and Cordoba (0.02 CO_2-eq./t soy-eq.) in central Argentina (Figure 3.5a). These two regions produce relatively high volumes of soybeans with around 10 million tons in 2017 and also ranked low in impacts of biodiversity and soil erosion compared to the other states (Table 3.1). While Santa Fe also had low water scarcity impacts, Cordoba had a median impact of around 250 m^3 world eq. per tonne soy.

For all studied impact categories, the variability within each state was quite high. Especially for the two largest producing regions in Brazil (Mato Grosso, Rio Grande do Sul), variability was large for LUC emissions ranging from 0.09-7.0 t/t and 0.1-4.2 t/t, respectively (Figure 3.5a). This variability is because soy-induced land use change within these states is distributed unevenly.

Table 3.1. Comparison of ranking of each major soy producing state, ordered by decreasing transformed forest area embodied in one tonne soy-eq. for each impact category studied. Numbers illustrate the ranking of each state with the number 1 (red) illustrating the largest impact and 28 (green) the smallest impact.

STATE	Producing Country	Land Use Change emissions	Biodiversity	Water scarcity	Soil erosion	Mean rank
SALTA	ARGENTINA	4	20	25	14	15.75
PARA	BRAZIL	1	22	10	5	9.5
RONDONIA	BRAZIL	2	12	23	13	12.5
PIAUI	BRAZIL	3	13	1	9	6.5
CAAZAPA	PARAGUAY	8	8	9	18	10.75
SANTIAGO DEL ESTERO	ARGENTINA	16	24	27	28	23.75
MATO GROSSO	BRAZIL	5	18	13	19	13.75
CHACO	ARGENTINA	9	21	28	24	20.5
CAAGUAZU	PARAGUAY	11	4	12	16	10.75
CANINDEYU	PARAGUAY	12	3	11	8	8.5
MARANHAO	BRAZIL	6	15	2	4	5.75
SAN PEDRO	PARAGUAY	18	7	6	20	12.75
SANTA CATARINA	BRAZIL	13	2	24	1	10
ALTO PARANA	PARAGUAY	17	1	18	11	11.75
BAHIA	BRAZIL	14	14	3	21	13
ITAPUA	PARAGUAY	10	6	17	10	10.75
PARANA	BRAZIL	20	5	20	3	12
TOCANTINS	BRAZIL	7	16	7	12	10.5
SAO PAULO	BRAZIL	23	10	19	15	16.75
MATO GROSSO DO SUL	BRAZIL	21	11	14	17	15.75
RIO GRANDE DO SUL	BRAZIL	19	9	22	2	13
LA PAMPA	ARGENTINA	26	23	5	26	20
ENTRE RIOS	ARGENTINA	15	26	26	22	22.25
MINAS GERAIS	BRAZIL	24	19	8	6	14.25
GOIAS	BRAZIL	25	17	16	7	16.25
BUENOS AIRES	ARGENTINA	22	25	4	25	19
SANTA FE	ARGENTINA	27	28	21	27	25.75
CORDOBA	ARGENTINA	28	27	15	23	23.25

3.3.3 Consuming nation perspective

3.3.3.1 Sourcing pattern across biomes

Sourcing patterns were quite variable across consuming countries. Many countries got the majority of their soybeans from high-producing Brazilian states (e.g. Mato Grosso, Parana, Rio Grande do Sul; Figure 3.6a). The two largest soybean consuming nations China and Brazil sourced in 2017 from these three states 50.7 % and 54.5 % of soybeans, respectively (Figure 3.6b). In contrast, other countries' production mainly came from Argentina (e.g. Santa Fe, Buenos Aires, Cordoba). These three departments produced the majority of soybeans for Vietnam (66.9 %), Indonesia (52.7 %), Italy (51.8 %) and Egypt (76.7 %). Only Turkey sourced large volumes from Paraguay, namely 46 % (mostly from Canindeyú and Alto Parana).

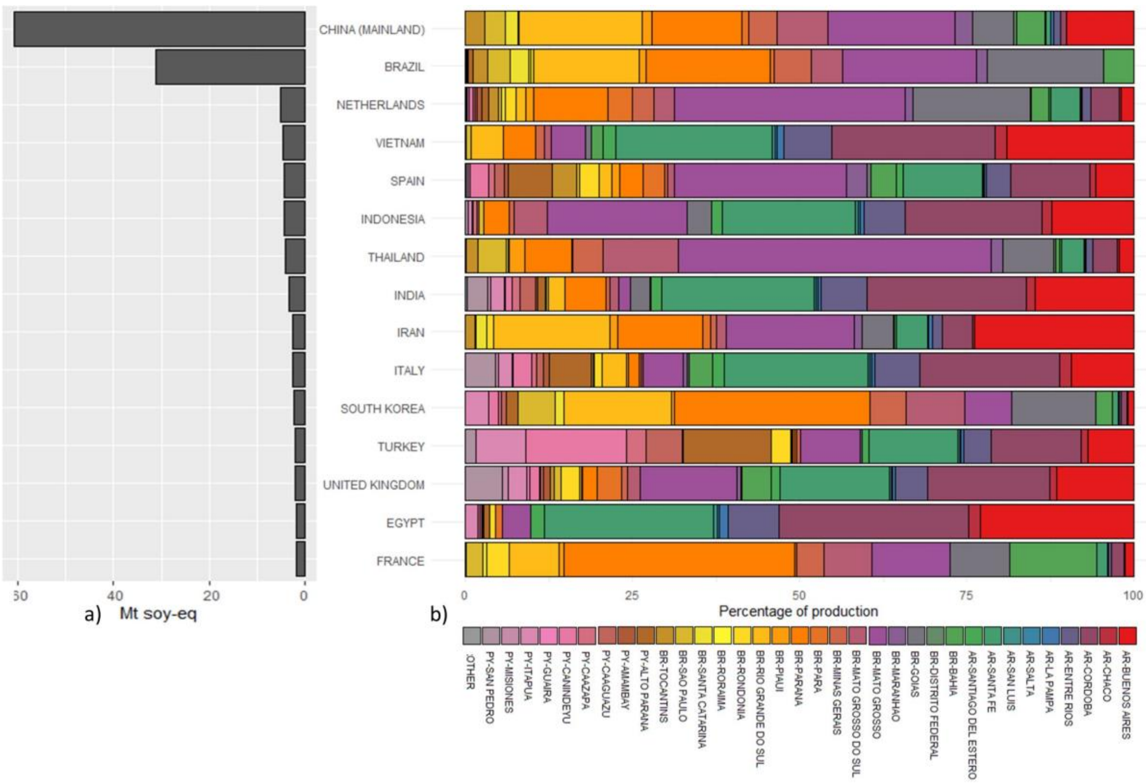

Figure 3.6: Soybean consumption for each major consuming country (a) and share of this consumption produced in the states across Brazil (BR), Argentina (AR) and Paraguay (PY) in 2017. States producing less than 1 % of production are grouped into 'other'.

The difference in sourcing patterns affected which environmental impact was largest for each consuming country. Sourcing larger shares from Mato Grosso in the Brazilian Cerrado resulted in larger land use change emissions (Figure 3.7a), whereas large shares from Parana and Rio Grande do Sul in the Mata Atlantica in southern Brazil led to larger biodiversity and soil erosion impacts (Figure 3.7b, d). In contrast, potential water scarcity was larger for consuming countries sourcing larger proportions from Buenos Aires and Cordoba in Argentina and Bahia in Brazil (Figure 3.7c). These geographical differences lead to differences in the environmental impacts per soy eq. For example, Spain had three times more land use change emissions (1.13 t CO_2-eq./t soy-eq) than India (0.27 t CO_2-eq./t soy-eq), Egypt (0.31 t CO_2-eq./t soy-eq) or Vietnam (0.26 t CO_2-eq./t soy-eq). These differences are due to Spain sourcing large trade volumes from municipalities within the Brazilian Mato Grosso state in the Amazon which is high in historical land use change. Countries with low land use change emissions sourced large trade volumes from the states of San Luis and Cordoba in Argentina (biomes of Pampas and Espinal (Figure S 2.5). In contrast, biodiversity impacts were largest for Brazil (14.3 x 10^{-10} PDF tonne^{-1}/t soy-eq) and France (14.0 x 10^{-10} PDF tonne^{-1}/t soy-eq) being around three times higher than for Egypt (3.9 x 10^{-10} PDF tonne^{-1}/t soy-eq). Here large biodiversity impacts were due to large shares of soy sourcing from southern Brazilian states such as Parana and Rio Grande do Sul in the Mata Atlantica biome (Figure S 2.5) where agricultural land conversion has left little habitat remaining for species.

Considering the two largest soybean consuming countries, China and Brazil, their different soy sourcing patterns lead to different estimated impacts (Figure 3.6). For example, China's small (10 %) share of soybeans from Argentina leads to higher water scarcity impacts per tonne (Table 3.2). In contrast, soybeans for Brazilian consumption are to a larger extent produced in the southern states of Brazil (e.g. Rio Grande do Sul, Goias, Parana) where soil erosion and biodiversity impacts are larger, but LUC emissions are lower. These differences are because Brazilian centres of domestic consumption are located in southern Brazil around cities like Sao Paulo and Rio de Janeiro where conversion for agriculture happened centuries ago and therefore land use change emissions are low while biodiversity impacts are high as little habitat is remaining for species. In contrast, Chinese supply chains are closely linked to the Pampa in Argentina where land use change happened more than 20 years ago but also the northeast of Brazil with more recent land conversion (Figure S 2.5).

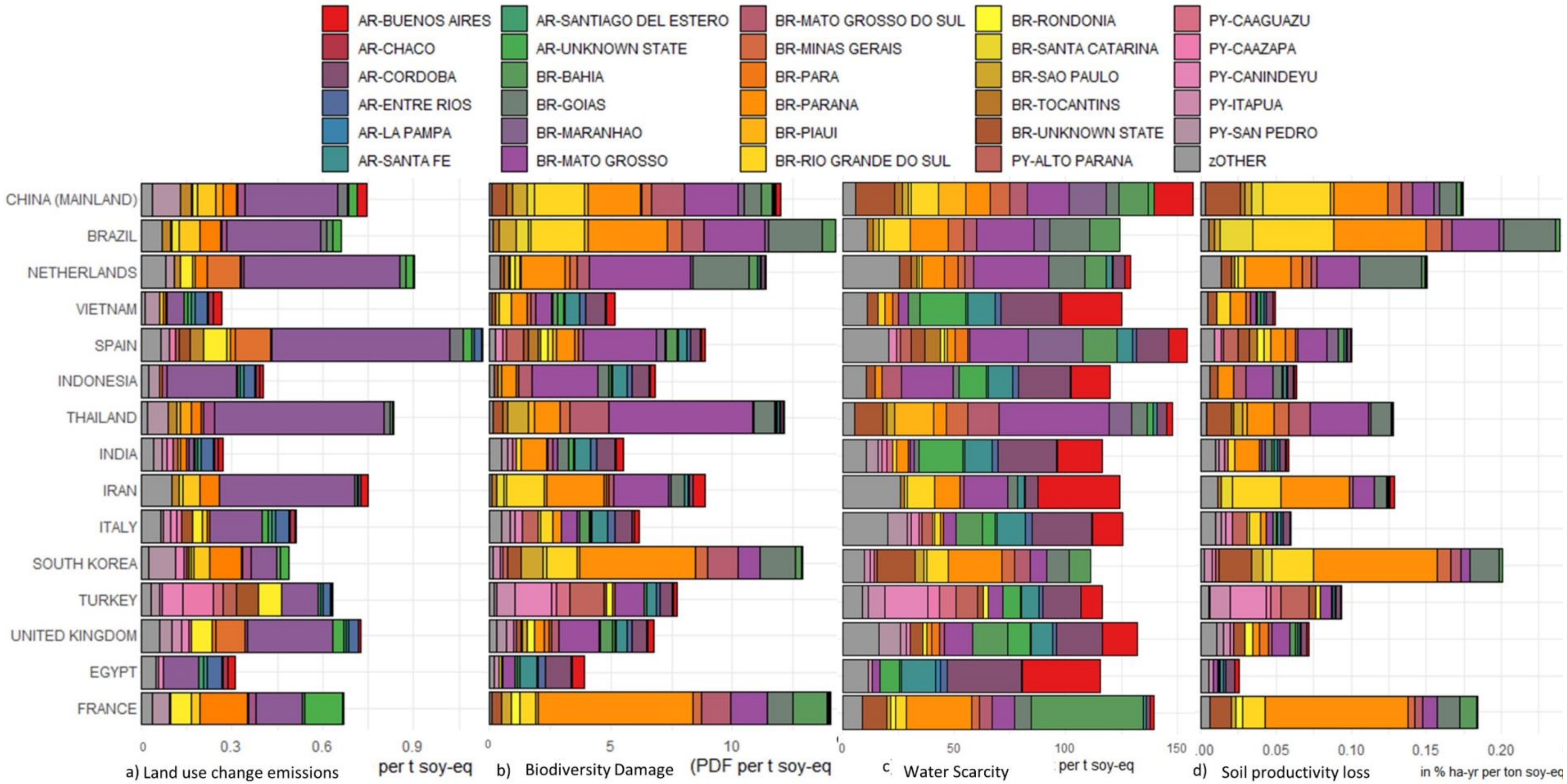

Figure 3.7. For the largest 15 soy consumer countries, as proportional contribution to each countries' export from producing states for four different impact categories , land use change emissions, as CO_2-eq. per soy-eq. (a) biodiversity damage, as Potentially Disappeared Fraction of Species (PDF) per soy-eq. (b), water scarcity footprint, as m^3 per soy-eq. (c) and soil productivity footprint, in % ha-yr per soy-eq (d). States producing less than 1 % of each consuming nation's soybeans were grouped into 'Other'. 'Unknown' means that no known sourcing state could be determined for these trade flows

Impacts per tonne for LUC emisisons and biodiversity are distributed across many municipalities for most consuming countries; whereas for water scarcity and soil erosion impacts per tonne are more concentrated (Figure 3.8). However, some countries have larger trade volumes from producing regions associated with high land use change emission. For example, for the Netherlands 25 % (n=153) of the soybean trade volume came from jurisdictions with land use change emissions above 1 t CO_2 per tonne; whereas for Vietnam, only 16 % (n=50) of sourcing jurisdictions had such high LUC emissions (see Figure S 2.6 for a comparison of different municipalities contributing cumulatively to different consuming countries land use change emissions).

Differences between studied environmental impacts are largest between soybean-induced LUC emissions and biodiversity. For biodiversity there are more municipalities which are relatively high in biodiversity but low in soy-induced LUC emissions (yellow/green colour Figure 3.8b). Although this pattern is more pronounced for some countries such as South Korea, France and Brazil. These differences between biodiversity and LUC emissions arise because some soybean producing regions (e.g. Mata Atlantica) experienced large-scale conversion to agriculture more than two centuries ago therefore leading to high biodiversity scores as little habitat is left though recent land conversion is low leading to small LUC emission scores.

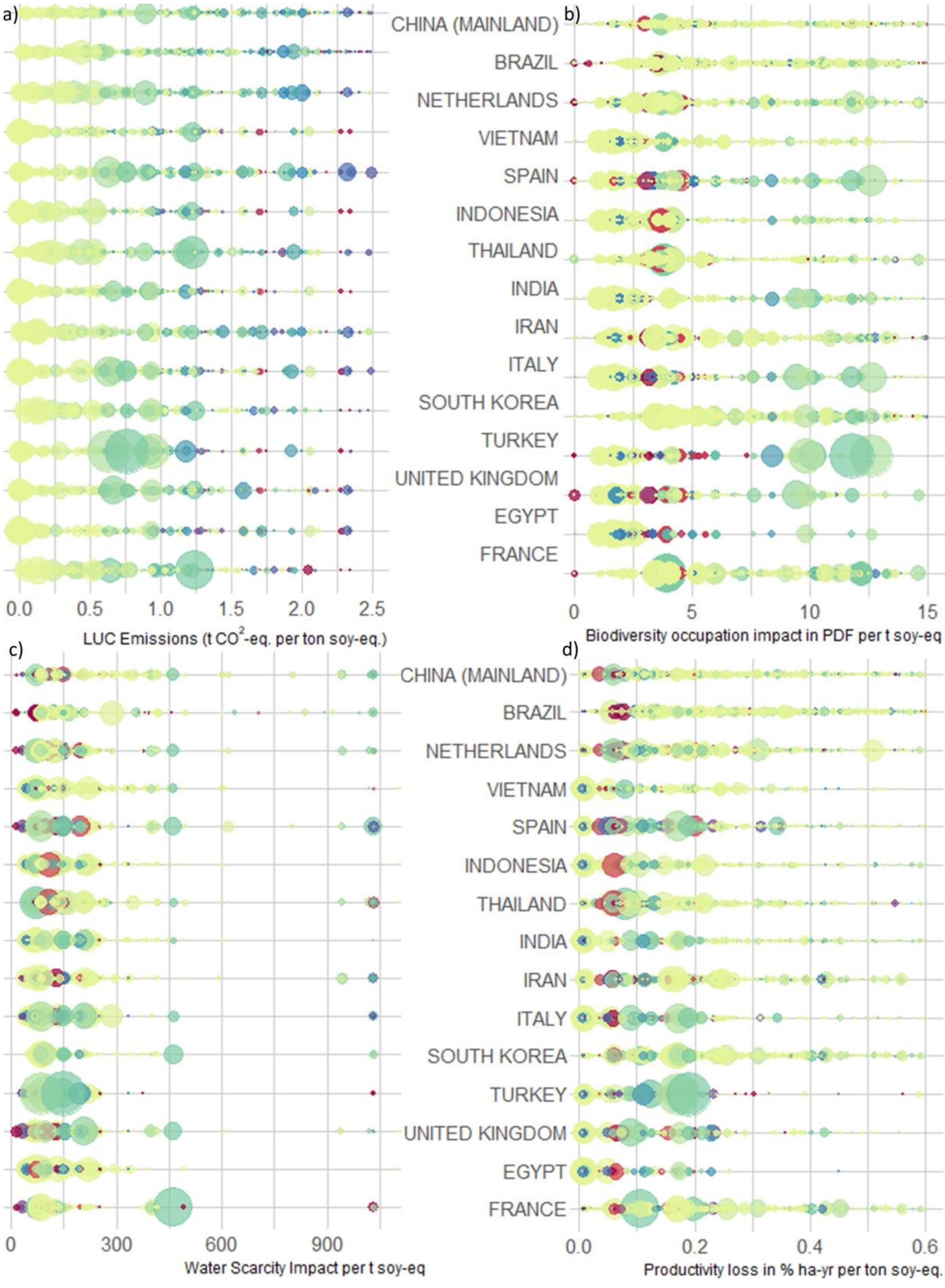

Figure 3.8: Distribution of impacts of land use change emissions (a), biodiversity occupation impacts (b), water scarcity (c) and soil erosion (d) for each major soy consuming country for each municipality sourcing region in Brazil, Argentina and Paraguay. Consuming countries are ranked by total soybean consumption volume in 2017. The bubbles' size illustrates the soybean trade volume, the colour the embedded deforestation area per tonne of soy eq.

Some countries' sourcing patterns resulted in low impact scores for all studied impact categories, while other countries' sourcing pattern resulted in low or medium impact scores for only few impact categories. Countries with lowest environmental impacts across all the considered impacts are Egypt, India and Vietnam. Consuming countries with small environmental impacts across all impact categories were sourcing considerable amounts from the Argentinian states Cordoba and Santa Fe which were characterized by low environmental impacts across all the four studied impact categories (Figure 3.4) and were ranked as the two lowest in terms of land use change emissions compared to all major State regions within Argentina, Brazil and Paraguay.

In contrast, countries with high impacts for almost all environmental impacts were France, China and Spain. For the two largest consuming nations, differences are largest for water scarcity as a larger share of Chinese soy is from Argentina (Figure 3.6).

Table 3.2. Comparison of ranking of each major consuming soy country in decreasing order from China (60 million tonnes soy in 2017) to France (1.9 million tonnes soy in 2017) for each impact category studied per tonne of soy eq. Numbers illustrate the ranking of each consuming country for each impact category with the number 1 (red) illustrating the largest impact and 15 (green) the least impact.

CONSUMING COUNTRY	Land Use Change emissions	Biodiversity	Water scarcity	Soil erosion	Mean rank
CHINA	5	5	1	4	3.75
BRAZIL	8	1	8	1	4.5
NETHERLANDS	2	6	6	5	4.75
VIETNAM	15	14	10	14	13.25
SPAIN	1	8	2	8	4.75
INDONESIA	12	10	11	11	11
THAILAND	3	4	3	7	4.25
INDIA	14	13	14	13	13.5
IRAN	4	7	9	6	6.5
ITALY	10	12	7	12	10.25
SOUTH KOREA	11	3	15	2	7.75
TURKEY	9	9	12	9	9.75
UNITED KINGDOM	6	11	5	10	8
EGYPT	13	15	13	15	14
FRANCE	7	2	4	3	4

3.4 Discussion

3.4.1 Implications for science

Benefit of spatial heterogeneity and coverage of multiple producing countries

The assessment of land use and land use change related impacts presented here complements and improves on existing estimates (e.g. Lathuillière et al., 2021; Escobar et al., 2020; Zu Ermgassen et al., 2020a) by consistently covering all major South American soybean producing countries and multiple impact categories at a high spatial resolution. The variability within biomes and states was extremely large across all studied impact categories. This variability is mostly due to the detail in the underlying LCI, which represent the variability in farming practices (e.g. double cropping, crop yield) and land use change dynamics (e.g. amount of land converted) but also due to spatial heterogeneity in the LCIA representing the variability in environmental characteristics (e.g. carbon storage in converted natural land, water scarcity, susceptibility of soils to erosion). Thereby my approach partly overcomes the limited spatial resolution of traditional environmental-economic accounting and Life Cycle Assessment methods (Gardner et al., 2019), revealing a large spatial variability in land use impacts of soy production across the three producing countries per unit of soy-eq. Nevertheless, variability for a small country like Paraguay can be much smaller than for a large country like Brazil. Especially for LUC emissions, water scarcity and soil erosion, variability within large Brazilian states (e.g. Mato Grosso, Para, Rio Grande do Sul) was larger than the variability within the entire country of Paraguay (Figure 3.5). (Note that Mato Grosso is twice as large as the area of Paraguay and produces three times more soybeans). The large range of values across the different impact categories and producing jurisdictions found here highlight the benefit of tracing commodities to municipality rather than state level to better identify impact hotspots for large countries like Brazil.

Comparison across biomes and states: trade-offs

While the conversion of non-woody vegetation might have little impact on greenhouse gas emissions, converting non-woody vegetation for soybean production can nevertheless lead to other environmental impacts such as biodiversity loss. I find that while soy-induced LUC emissions is largest for the forest-biomes Amazon (Brazil), Chaco (Argentina) and Mata Atlantica in Paraguay (Figure 3.3), biodiversity impacts are also high in non-forested biomes such as the Pampa or the Cerrado (Figure 3.4). This illustrates that while LUC-driven impacts in LCA are only emerging and still highly discussed (e.g. Lueddeckens, Saling and Guenther, 2020), the current focus of assessing land use change impacts in LCA and footprinting mostly in terms of greenhouse gas emissions and increasingly biodiversity (De Rosa, 2018), might lead to trade-offs with other sustainability challenges. While the current focus is on global impacts such as accelerated climate change and global species loss (e.g. Chaudhary and Brooks, 2018), few LCA studies consider the local impacts of land use and land use change (LULUC) (De Rosa, 2018) and the multifunctionality of ecosystems (Othoniel et al., 2016). To my knowledge this is the first study which studies impacts of LULUC on soil erosion in addition to greenhouse gas emission and biodiversity impacts. Some states were identified as soil erosion hotspots which would have not been identified as hotspots if only LUC emissions were considered (e.g. Santa Catarina, Rio Grande do Sul; Figure 3.5). Therefore, methods need to account for the quality of the converted natural land expressed in changes to biodiversity or ecosystem services (e.g. water provisioning, sediment retention, nutrient cycling) as well.

Comparison to other studies

The length of the land use change amortisation period and the native vegetation type being converted can change which geographic regions get identified as 'hotspots'. For instance, taking a 3-year allocation time period Escobar et al. (2020) found higher soy-induced LUC emissions for the Cerrado (0.51 CO_2-eq./t soy-eq) than the Amazon (0.3 CO_2-eq./t soy-eq). In contrast, in this study the Amazon (3.5 CO_2-eq./t soy-eq) had higher emissions from soy-induced LUC compared to the Cerrado (0.56 CO_2-eq./t soy-eq). These differences are likely because my LUC amortisation period (1996-2016) included the early 2000s in which deforestation rates in the Amazon were much higher than in the time period of 2010-2015 which Escobar et al. (2020) studied (see Chapter 4 for a detailed analyses of the effect of land use change amortisation periods on soy-induced LUC emissions). However, Song et al. (2021) had a broader geographic scope including soy-induced land conversion in all South American countries and a longer time-period (2001-2016) and identified the 14 municipalities with the largest soy-induced deforestation in the states of Mato Grosso (Brazil), the MaToPiBa states (Brazil), but also Salta and Santiago del Estero (Argentina). Therefore, the deforestation hotspots identified by Song et al (2021) overlap with the deforestation hotspots identified in this chapter except for Caazapá in Paraguay which I identified as deforestation hotspot as well. However, Song et al (2021) did not account for the carbon-density of these converted forests. While I found in this study that Salta experienced the highest forest area loss allocated to one tonne of soybean eq., forests in Salta store less than a third of the aboveground carbon (19 Mg/ha) than the tropical moist forests in the Amazon being converted in Mato Grosso (66 Mg/hectare; Table S 3.1).

Choice of indicator: Spatial resolution of indicator

Due to the complexity of biodiversity, inclusion into LCA is challenging (see e.g. Curran et al., 2016). In line with the life cycle initiative lead by UNEP SETAC, I have followed their guidance for Life Cycle Assessment and applied the indicator developed by Chaudhary and Brooks (2018) to account for land use impacts on biodiversity. This indicator was selected during a consensus finding process as at that time it was the best available (Teixeira et al., 2016) in terms of global coverage, based on scientific models of species richness, weighting of vulnerability (IUCN threat) and irreplaceability (rarity) and stakeholder understandability (Chaudhary et al., 2015). However, whereas this indicator has the advantage of being simple and therefore easily applicable, it also has several shortcomings according to a recent critical review by Crenna et al. (2020). Firstly, it is limited by its spatial resolution to the ecoregion level: assuming the same impact for any region within one ecoregion. While this simplification might be acceptable for small ecoregions (depending on the purpose of the study), for large ecoregions such as the Cerrado this limits the ability to understand the variability of impacts within the biome. For example, Green et al. (2019) showed that within the Cerrado there is a huge spatial variability in threats to species and therefore differences in soy sourcing patterns result in different biodiversity footprints between consuming countries. Another limitation of expressing biodiversity impacts in 'Potentially Disappeared Fraction' (PDF) is that it only describes species loss but does not account for the multi-dimensional nature of biodiversity (e.g. genetic, ecosystem diversity or species abundance). As Marquard et al. (2019) found that the choice of biodiversity indicator can affect the outcome of the study, decision-making should be guided by multiple biodiversity indicators. However, as indicators should preferably also allow data users to monitor and report progress towards targets (Durán et al., 2020) finding easily available data to do this is a challenge.

Besides biodiversity, different water footprints exist and which indicator is best is highly discussed (e.g. see Hoekstra, 2016). It has to be noted that AWARE only ascribes potential impacts to blue water consumption (i.e. irrigation) but not to green (i.e. rainwater) water consumption. A recent study by Caldeira et al. (2018) compared results applying the AWARE water footprint to the water stress footprint method by Ridoutt and Pfister (2013) which accounts for green water and found no significant difference in the relative ranking between different growing regions of vegetable oils. Therefore, I believe that for the purpose of this study (comparing different soybean production areas) the AWARE indicator is suitable.

Global data vs national data: Balancing coverage with accuracy

Using data with global coverage or spanning long time periods such as ESA CCI for land cover or Baccini et al. (2012) for carbon density can sometimes be less representative of local characteristics. For example, Pötzschner et al (2022) found that global biomass maps underestimate carbon density in the Gran Chaco by between seven and 14 times. There is also uncertainty in different global forest carbon datasets. In the wet tropics (15°S – 10°N), Santoro et al. (2021) found 10 to 50 % less carbon compared to the Baccini et al. (2012) dataset which Escobar et al. (2020) and Pendrill et al. (2019b) used. However, Santoro et al. (2021) compared all these AGB datasets to the plot-level inventory and found that Baccini et al. (2012) overestimated the AGB in the southern hemisphere wet tropics by 25 to 60 % and outside of the wet tropics by 20 to 160 % whereas their own dataset only had few percentage-points difference. Therefore, I believe that the Santoro et al. (2021)

dataset is more reliable (see Chapter 4 for sensitivity of results to different carbon density data). This illustrates that more consensus building might be needed about which land cover maps should be used to report progress towards ambitious targets, and also highlights the requirement for researchers to make clear where uncertainty associated with their data lies.

Limitations of this study

Uncertainty in regionalized LCA results can be due to a lack of spatially-refined inventory data or spatial variability in the characterization of the impact assessment (Patouillard et al., 2018). In my case study, there was especially a lack of spatially-explicit inventory data which increases uncertainty in results. For example, uncertainty in spatially-explicit farming practices such as double-cropping (occupation time, LCI), irrigation volumes (water consumption volume, LCI) and no-tillage soil management practices (crop management factor, LCI) may affect confidence in the impact assessment results. But there was also uncertainty in land cover maps (land transformation, LCI) and biomass density estimates affecting especially land use change emissions. However, sub-national agricultural information (e.g. double-cropping, yield) was derived from key governmental production statistics therefore considered reliable (Trase, 2020). Nevertheless, Patouillard et al. (2018) argued in their review that there is a balance between time-consuming spatialization of LCA and acceptable uncertainty due to spatial detail. Another source of uncertainty is the year-to-year variability in supply chain configurations of countries. In this chapter I only estimated impacts due to the supply chain configuration in one year (2017). However there might be some variability in estimated impacts because of the year-to-year changes in supply chain configuration. Nevertheless, a recent study found that at least in Brazil supply chains are 'sticky' over a time period of 5-10 years (Reis et al., 2020). It also has to be noted that this approach is not accounting for re-exports (Trase, 2018) and thus impacts are attributed to the first country of import. Therefore, this approach likely overestimates the impacts of countries like the Netherlands importing directly large volumes of soybeans from South America whereas land-locked countries like Austria import low amounts of soybeans directly.

My results, despite including more impact categories than previous studies (e.g. Escobar et al., 2020), only include impacts from land occupation and land transformation until the farm-gate stage of the supply chain. Therefore, I have not accounted for emissions from agricultural cultivation, processing and transport. However, as most impacts from land use, land use change and water consumption are in the agricultural stage (Clavreul et al., 2017; Milà I Canals, Rigarlsford and Sim, 2013), I am confident that this focus is acceptable for impacts on biodiversity, water scarcity and soil erosion. Nevertheless, for LUC emissions, sub-national jurisdictions also differ in their transport- and soy-farming emissions (Escobar et al., 2020; Castanheira and Freire, 2013). However, as Escobar et al. (2020) showed that the variability between states in Brazil is much larger in emissions from land use change than emissions from agricultural cultivation of soybeans, the focus here was on emissions from land use change.

3.4.2 Implications for policy

Differences between consuming countries and implications for policy

This study showed that there are differences between soybean consuming countries in impacts from land use and land use change as a result of different sourcing patterns. The findings here on South American soy adds to existing soybean LCAs by expanding the scope to include more than a single producing country (often Brazil) to allow consistent comparison across multiple producing countries (see gap identified in stakeholder interviews, see Chapter 2). All three producing countries studied here are among the five largest soybean producers globally and Brazil additionally is one of the world's largest soybean consumers (FAOSTAT, 2020). Therefore, it was a promising step that Brazil, Argentina and Paraguay all endorsed the Glasgow Declaration aiming to end net forest loss by 2030 (UN, 2021) even though none of them had previously endorsed at the national level the New York Declaration on Forests (NYDF) (UN, 2019). However, despite these pledges, deforestation rates in the Brazilian Amazon have accelerated in recent years (WRI, 2020) which brings into question Brazil's real intent. Nevertheless, consuming countries also have responsibility for impacts, since one of the key drivers of tropical deforestation is trade in agricultural and forestry commodities (Pendrill et al. 2019b). Many signatories of the NYDF were identified as large contributors to land use and land use change impacts in this study (such as UK, Germany, Netherlands and Italy). However large identified contributors such as China and Spain have also now endorsed the Glasgow Convention on Forests, which might be an encouraging sign for land use trajectories. Nevertheless, among the fifteen largest soy exporters studied here there are also consuming countries with sourcing patterns linked to soy-induced LUC emissions which have neither endorsed the Glasgow nor the NYDF: Thailand and Iran. Therefore, there is the risk of supply chain leakage (Lambin et al., 2018) as producers continuing to expand soy production to new land would still find buyers accepting those soybeans with high environmental impacts.

Additionally, I found here that geographic hotspotting focusing only on LUC emissions misses geographic hotspots of biodiversity loss, water scarcity or soil erosion. While the New York Declaration focused only on forests, the Glasgow convention is broader in scope aiming to "conserve forests and other terrestrial ecosystems"[21]. However, this ambition has so far not been followed by the EU's proposal for a regulation on deforestation-free products which only includes 'forests', shrubland and other wooded land but excludes grasslands and wetlands such as the Pampa (WWF, 2022). Additionally, to avoid leakage into other ecosystems such as wetlands, the EU might want to include other ecosystems as well when this proposal will be reviewed in a few years (European Parliament, 2021). While the EU's 'Farm 2 Fork' strategy is also ambitious in aiming to reduce footprints on natural resources like water and soils, so far there are a lack of measurable performance indicators (WRI, 2021) available to monitor progress towards targets and to hold countries accountable). Harris et al. (2021) published a framework that allows the consistent and annual monitoring of forest conversion emissions across the world that would allow to monitor progress towards countries' targets. However, governments will still rely on the private sector to implement those ambitions.

3.5 Conclusions

The complexity of supply chains and the variety of potential environmental impacts associated with internationally traded agricultural commodities create challenges for climate change mitigation and the sustainable use and governance of natural resources. I incorporated sub-national supply chain mapping data from the Trase platform into LCA methods to identify geographic hotspots of environmental impacts in agricultural supply chains at a high spatial resolution and analyse multiple impact categories simultaneously. Taking soy as an example, the research demonstrated that environmental hotspots are distributed unevenly: hotspots of LUC emissions in Brazil are in the biome of the Amazon (states of Para and Rondônia) and the Cerrado (Maranhao, Piaui), whereas hotspots of biodiversity damage are in the Mata Atlantica stretching across southern Brazil (Santa Catarina, Parana, Rio Grande do Sul) and Paraguay (San Pedro). In contrast, hotspots of water scarcity are in the northeast of Brazil (Maranhao) and Argentina (Cordoba, Salta, Buenos Aires) and hotspots of soil erosion are located in southern and south-eastern Brazil (Santa Catarina, Rio Grande do Sul and Minas Gerais). These differences between soy producing states also affect which consuming markets had the largest footprints, which is dependent on their sourcing pattern: Brazil, sourcing domestically mostly from southern Brazil, had the largest soil productivity loss (0.24 %

[21] https://ukcop26.org/glasgow-leaders-declaration-on-forests-and-land-use/

yield loss/tonne^{-1}) and biodiversity footprint (14.3 x 10^{-10} PDF/t soy-eq); Spain, sourcing high shares from Brazilian central west, had the largest LUC carbon footprint (1.13 t CO_2-eq./t soy-eq); and China, sourcing high shares from the northeast of Brazil and Argentina, had the largest water scarcity footprint (157 m^3/t soy-eq). However, the spatial variability of all four impact categories was large within many states, highlighting the need for traceability of commodity supply chains to municipality- rather than state-level for robust impact assessments where possible.

A key contribution to knowledge in this Chapter is the consistent application of available data and use of multiple environmental sustainability indicators across three major producing countries in South America, with high spatial and supply-chain specific disaggregation. This information can be used by multi-national companies and consuming nations to identify environmental impact hotspots in supply chains (Aké and Boiral, 2022), manage trade-offs between different dimensions of environmental sustainability and identify partnerships with actors sourcing from similar jurisdictions to collaborate on sustainability challenges. The LUC emission estimates particularly could be incorporated into commonly used LCA software to provide spatial detail without consuming additional time of LCA practitioners. The approach developed in this chapter can also help to prioritise efforts to improve the 95ork95ulture95ion of Life Cycle Assessment. To this end, more research is also needed to understand the sensitivity of the estimated impacts to different data and methodological choices to improve the robustness of environmental impact footprints of agricultural commodities.

Chapter 4Sensitivity Analysis

The influence of methodological and data choice in the assessment of water use, land use and land use change impacts: example from South American soybean production

Abstract

Improvements in the traceability and transparency of supply chains together with satellite remote sensing have improved the ability to quantify land use and land use change impacts of agricultural production linked to trade. However, so far, most research focuses on the uncertainty of input data (e.g. yield), whereas relatively little research exists on the sensitivity of methodological choices on LCA results. In particular, methods to quantify land use and land use change impacts are highly debated, leading to different results depending on choices made in the application of methods.

In this study I test methodological choices, alternative data sources and assumptions on farming practices on the sensitivity of land use change emissions, biodiversity damage, soil productivity loss and water scarcity linked to South American soybean production and trade. I find that choosing a 5 year timeframe to amortise land conversion and emissions instead of 20 years triples land use change (LUC) emissions for some states outside of the Amazon. Similarly, the use of an alternative forest carbon dataset doubles LUC emissions mostly for states in Argentina and Paraguay. Biodiversity damage is most influenced in the Pampa by the inclusion of grassland land cover in the transformed area. Water scarcity is more influenced by the spatial variability between states than the temporal 96ork96ulturn of the monthly water scarcity. In contrast, soil productivity loss is more influenced by the adoption of alternative assumptions on farming practices (tillage) than the spatial variability between states. This study illustrates that besides the inclusion of more spatially-resolved data to enhance the accuracy of impact assessments, there also needs to be more consensus building and harmonisation to agree on methodological choices and data to consistently measure land use and land use change related impacts of imported commodities to support policy.

4.1 Introduction

Decision makers in companies and governments increasingly rely on LCA to guide decision-making towards reducing impacts of food production on climate, water and biodiversity (Lueddeckens et al., 2020). However, according to Poore and Nemecek (2018), there is a lot of variability in the environmental impacts of agricultural production. These authors found that 42 % of the variance of agricultural emissions of products is due to land use change and farming on organic soils. Yet, despite emissions of LUC contributing around 8 % to annual global greenhouse gas emissions (Ritchie, Roser and Rosado, 2020), there are no agreed detailed standards on how to quantify greenhouse gas emissions from LUC and how to allocate these to different commodities and actors. Variability in LCA estimates of agricultural products is inherently larger compared to other products (Heijungs, 2020). This is due to multiple factors such as the natural variability in the seasonal climate, ecological factors (e.g. precipitation, soil type, natural ecosystems) but also methodological choices such as the spatial resolution (Donke et al., 2020), the land use change (LUC) amortisation period (e.g. Schmidt, Weidema and Brandão, 2015) or the allocation of LUC emissions to products and territories (Bhan et al., 2021). However, most research to date has focused on the uncertainty of life cycle inventory data (e.g. yield, irrigation water use), whereas relatively little research has been done on the sensitivity of methodological choices on LCA results (Rosa et al. 2018). Some methodological choices are highly debated due to their complexity, considerable data requirements and value-based assumptions (Rosa et al. 2018). This lack of consensus has led to a wide range of different results (e.g. Ahlgren and Di Lucia, 2014), illustrating the large uncertainty in estimates which can reduce the credibility of LCA results by decision-makers (Igos et al., 2019).

Soybeans are a versatile ingredient for many sectors and imported in large quantities though are increasingly being associated with detrimental impacts in producing regions (Kastner et al., 2021). Therefore, robust estimates of carbon and other environmental footprints are needed. However, as an example, reported land use change emissions can vary largely depending on differences in data and methodological choices. Existing research found that there is a large variability in reported greenhouse gas emissions of soybeans largely due to regional differences in land use change emissions, ranging from 0.1-17.8 t CO_2-eq./t soy-eq in Castanheira and Freire (2013) and 0.1-29.47 t CO_2-eq./t soy-eq. in Escobar et al. (2020). A recent study found that 86 % of greenhouse gas emissions of Brazilian soybean oil is from LUC when considering all life cycle stages from agricultural production to retail (Liao et al., 2020). Therefore, understanding how methodological choices and different available datasets affect the variability in impacts of land use and land use change for soy production, is crucial to identify which actions could be taken to reduce environmental impacts.

In this study, I made use of subnational production and trade data aimed at improving the transparency of commodities within globalized supply chains as well as spatially-explicit global land cover maps covering the period from 1992-2015 (ESA CCI, 2017). Even though studies have previously analysed the spatial variability of LUC emissions linked to commodity supply chains (e.g. Escobar et al., 2020), there are a lack of studies analysing the influence of different methodological choices, input data and uncertainty in LCIA models on final results.

An 'amortisation period' refers to the time period over which emissions from land conversion are spread over production in the subsequent years after land conversion. This approach is adopted instead of the (often less equitable) approach of allocating all of the emissions to the first crop harvested after land conversion. This length of the amortisation period is one of the most debated methodological choices in estimating LUC impacts (De Rosa et al. 2018). Standards such as the Greenhouse Gas Protocol (WRI/WBCSD, 2011) and FAO guidelines for feed supply chains (LEAP, 2016) specify that LUC emissions of agricultural products should be estimated over a timeframe of 20 years and use spatially-explicit data. However, due to a lack of land cover maps spanning a decadal time period (Kulak et al., 2018), studies estimating LUC emissions of crops frequently choose shorter amortisation periods (e.g. Escobar et al., 2020). Nevertheless, recently land cover maps were developed covering consistently long time frames at annual time steps from 1992-2015 (ESA CCI, 2017). This dataset would allow testing of the sensitivity of LUC emissions to different amortisation periods.

While LUC impacts are most frequently expressed in greenhouse gas emissions, impacts of LUC on other impact categories are less often estimated (De Rosa, 2018). A framework on how to quantify land use impacts on biodiversity in LCA (Koellner et al., 2013) defined that total biodiversity impacts are due to both land occupation (using land) and land transformation (changing the land use). However, due to the ongoing debate on how to quantify the amount of transformed area, multiple recent studies on biodiversity impacts in LCA excluded impacts from land transformation (e.g. Lucas et al., 2021; Lathuillière et al., 2021). Therefore, better understanding is needed on whether for the identification of geographic hotspots of biodiversity impact, focusing on land occupation is sufficient or whether including land transformation leads to different conclusions about the geographic hotspots of concern.

As many LCA studies are limited in their spatial and temporal resolution (Hellweg and Milà I Canals, 2014), often due to limited availability of data, selecting reliable data that balances detail and time-efficiency is a challenge (Patouillard et al., 2018). All global cropland land cover maps are known to be associated with some uncertainty in their classification of different land cover types (Pérez-Hoyos et al., 2017). I chose the global ESA CCI maps as they consistently cover the producing regions of interest. However, these land cover maps do not differentiate between pasture and natural grassland limiting the reliability of estimates of biodiversity impacts from land transformation. While this differentiation between managed and natural grassland is less relevant for estimating LUC emissions (Chang et al., 2021), it introduces uncertainty when estimating biodiversity impacts from land conversion. Especially for natural grassland such as the Pampa in Brazil or the Espinal in Argentina. Another limitation of the ESA CCI classification is that they have one land cover type referred to as 'mosaic of agriculture' where it is not known how much within each pixel (300x300m) is natural land and how much is agriculture. Therefore, here I tested the sensitivity on biodiversity impacts of including grassland and mosaic of agriculture on the amount of land transformation on LUC emissions.

Besides land cover, alternative data sources were available with lower spatial resolution (forest carbon density and double-cropping) and higher temporal resolution (water scarcity characterization factors, CFs). Here, these alternative data sources were selected for sensitivity analyses as these three alternative data were available and considered as possibly having high influence on the results.

In this chapter, I assess the sensitivity of results to four key challenges in the assessment of commodities with complex globalized supply chains within an LCA framework (Figure 3.1):

- Methodological choices: LUC amortisation period, inclusion of land cover types and inclusion of transformation impacts
- Data choices: carbon storage in forest land cover types and double-cropping
- Uncertainty in LCIA models: soil productivity loss from water erosion
- Uncertainty in inventory data: soil tillage

Table 4.1. Sources of uncertainty for which sensitivity was studied for each of the different impact **categories.**

	LUC emissions	Biodiversity	Water scarcity	Soil productivity loss
Methodological choices	• Amortisation period • Inclusion of 'Mosaic of Agriculture' in transformation area	• Inclusion of transformation impacts • Inclusion of 'grassland' in transformation area		
Data choices	• Non-spatially explicit forest carbon		• Monthly extremes	
Uncertainty in LCIA models				• Min and Max from Sonderegger and Pfister (2021)
Uncertainty in inventory data				• Assumptions on tillage practices

4.2 Materials and methods

As explained in Chapter 3, I combined physical trade flow analyses with Life Cycle Assessment principles (see Figure 3.1) to evaluate embedded impacts in trade of one tonne of soybean produced across Argentina, Paraguay and Brazil (see map in Figure 3.2). Again, the advanced physical trade accounting model 'Spatially-Explicit Information on Production to Consumption Systems' (SEI-PCS) developed by Trase was used to trace through global commodity supply chains countries of import to the sub-national region of production (Godar et al., 2016; Godar et al., 2015). Environmental impact categories included Land use change emissions, Biodiversity Damage Potential, Water scarcity and Soil Productivity Loss. The functional unit was one tonne of soybean leaving the farmgate. During the application of the LCA approach in Chapter 3, I had to make assumptions and choices which created uncertainty. Therefore, in this chapter, I build on the previous Chapter 3 by testing the sensitivity of results to methodological choices, alternative data sources and uncertainty in inventory data and life cycle impact assessment model parameters.

4.2.1 Methodological choices

4.2.1.1 Amortisation period of LUC emissions

To compare the consequences of different land use change amortisation periods (AP) on carbon emissions, I used the land cover map provided by ESA CCI covering consistently long time frames at annual time steps from 1992-2015 (ESA CCI, 2017). This allowed the mapping of historical land cover 20 years (1996), 10 years (2006) and 5 years (2011) before the soy planting in 2016 for the harvest in 2017. Changes in carbon stocks of land converted to soy production and emitted to the atmosphere as greenhouse gas emissions GHG_{LUC} (Eq. 1) in t CO_2 eq. ha^{-1} yr^{-1} were calculated as follows (Lam et al., 2021):

$$GHG_{LUC,j} = \frac{CS_{j,tAP} - CS_{j,t0}}{AP} * CO * t_{occ} \quad (1)$$

Where $CS_{j,tAP}$ are the carbon stocks before land conversion and $CS_{j,t0}$ are the carbon stocks during cultivation with soybeans (in t C ha^{-1}) in each soybean harvested pixel *j* at time *t*; *AP* the amortisation period for annualising LUC emissions (in years), t_{Occ} is the duration of the occupation process (i.e. 1 if single-cropped and 0.5 if double-cropped) and CO the conversion factor for converting C to CO_2, following Lam et al. (2021).

4.2.1.2 Including land transformation in biodiversity impact

Following Chapter 3, to assess biodiversity impact I used the indicator developed by Chaudhary and Brooks (2018) as recommended by the Life Cycle Initiative (UNEP SETAC). In LCA, impacts of land use on biodiversity are due to land occupation (using land) and land transformation (changing the land use) according to Koellner et al. (2013). As the estimation of the amount of transformed area is uncertain and highly debated, I tested the sensitivity of including transformation impacts additionally to occupation impacts on biodiversity (see Supplementary Information Chapter 4, Equation 7). To calculate transformation impacts, I used the CFs provided by Chaudhary and Brooks (2018) which they derived by multiplying the occupation CFs with half of the regeneration time of each ecoregion to the natural state (Supplementary Information Chapter 4, Equation 8). The CF of transformation from Chaudhary and Brooks (2018) is expressed in Potentially Disappeared Fraction (PDF) of species per m^2yr^{-1} and available for each ecoregion of the world (see Table S 2.3). To calculate transformation impacts on biodiversity, the amount of transformed area (inventory) already estimated for LUC emissions over a 20-year amortisation period was taken (see section 3.2.2).

4.2.1.3 Land cover classes

To estimate the area of change for each land cover type converted to soybean within each municipality and biome, the raster of soybean harvested area (30 x 30 m) was overlaid with ESA CCI land cover maps (300x300 m) of the years 1996, 2006 and 2011 and administrative shapefiles (DIVA-GIS, 2019) using code developed within the Google Earth Engine platform. To simplify the land cover analyses, I grouped the original 28 ESA CCI land cover classes into the seven land cover classes further analysed and referred to in this study (see Table 4.2 and Figure 3.2). To reduce the error in the land cover change analyses, I excluded in the 'base case' (choices taken in Chapter 3) the ESA pixels classified as 'mosaic agriculture' (classes 30 and 40) and only considered pixels which are 100 % natural land (all classes 50 to 210). This procedure followed the approach taken by Eigenbrod et al. (2020) who used ESA CCI maps to analyse global cropland expansion. However, as in this study the soybean raster has a finer resolution than the ESA CCI maps, it is possible that within the mosaic of agriculture pixel (300x300m) some natural land was converted to soybeans (30x30m). Therefore, here I tested the sensitivity of including mosaic of agriculture (classes 30 and 40) on the soy-induced transformed area and related carbon emissions results. Another limitation of the ESA CCI land cover map is that the land cover grassland (class 130) does not differentiate between managed and natural grassland. Therefore, I tested the sensitivity of excluding conversion from grassland in the biodiversity impacts.

Table 4.2. Definitions of the ESA CCI land cover classes (UCL Geomatics, 2017) as prevalent in countries analysed in this study and aggregation into land cover classes used in this study for LUC analyses.

ESA LU class	Definitions of land cover class	Simplified land cover class used in this study	Included in LUC Analyses?
10, 11, 12	Rainfed cropland	Cropland	No
20	Irrigated cropland		
30	Mosaic cropland (>50 %)/ natural vegetation (tree, shrub, herbaceous cover) (<50 %)	Mosaic of Agriculture	Not in Base Case
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50 %)/ cropland (<50 %)		
50	Tree cover, broadleaved, evergreen, closed to open (>15 %)	Forest	Yes
60, 61, 62	Tree cover, broadleaved, deciduous, closed to open (>15 %)		
100	Mosaic tree and shrub (>50 %)/ herbaceous cover (<50 %)	Mosaic of Natural Land	
110	Mosaic herbaceous cover (>50 %)/ tree and shrub (<50 %)		
120, 121, 122	Shrubland	Shrubland	
130	Grassland	Grassland	
150, 151, 152, 153	Sparse vegetation (tree, shrub, herbaceous cover) (<15 %)	Rest	
160	Tree cover, flooded, fresh or brakish water	Forest	
170	Tree cover, flooded, saline water		
180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water	Shrubland	
190	Urban areas	Rest	
200, 201, 202	Bare areas		
210	Water bodies		

4.2.2 Data Choices

I tested the sensitivity of results to alternative data sources with lower spatial resolution (carbon storage in forest, double-cropping) and higher temporal resolution (water scarcity indicator) (Table 4.3) compared to data used in the base case (Table 4.4). In Chapter 3, I selected for all non-forest land covers (class 100-210) carbon values from Ruesch and Gibbs (2008) but for forest (classes 50-62 and 160-170) I considered the GEOCARBON dataset (Santoro et al., 2021) to be more reliable as it is spatially-resolved (100x100m). Therefore, in this chapter, I tested the sensitivity of the LUC carbon results to choosing alternative forest carbon values from Ruesch and Gibbs (2008) that describe forest carbon values spatially differentiating only for four different ecofloristic zones across the studied producing countries (see Table S 3.2). Similarly, in Chapter 3, I considered the national and more recent data for double-cropping to be more robust compared to an alternative dataset published by Waha et al. (2020). Waha et al. (2020) is based on field data from the year 2000 at a resolution of 50 arc-minute (~56 km at the equator). Therefore, in this chapter, I tested the sensitivity of using the Waha et al. (2020) dataset to account for double-cropping in the allocation of LUC impacts to crops (see Eq. 1). For water scarcity, I chose in Chapter 3 the CFs aggregated for agriculture to one year (Boulay et al., 2018) due to a lack of information about the most likely month of irrigation. However, as water scarcity footprints should ideally be assessed on a temporally explicit basis (ISO 14046, 2014), I tested the sensitivity of my results to monthly extremes during the growing season of soybeans (November to June) using the monthly 'AWARE' water scarcity characterisation factor developed by Boulay et al (2018). I used the monthly water scarcity CF available for each watershed.

Table 4.3. Alternative data used (used in the sensitivity analyses)

Parameter name	Spatial resolution	Temporal resolution	Geographic coverage	Empirical data from	Source
Carbon storage	Ecofloristic zone	NA	Global	2000	Reusch and Gibbs (2008)
Water scarcity CF	Watershed	Month	Global	2010	Boulay et al. (2018)
Double-cropping	30 arc-minute	NA	Global	2000 (1998-2002)	Wada et al (2020) based on data from Monfreda et al. (2008)

Table 4.4. Data used in base case

Parameter name	Spatial resolution	Temporal resolution	Geographic coverage	Empirical data from	Source
Forest AGC (Aboveground Carbon)	100x100 m	NA	Global		GEOCARBON (Santoro et al., 2021)
Water scarcity CF	Watershed	Year	Global	2000	Boulay et al. (2018)
Double-cropping	Municipality	Year	Country	2017	IBGE (2018), INBIO (2017); Ministry of Agriculture Argentina (2017)

4.2.3 Uncertainty in the Inventory and LCIA model

I studied the uncertainty due to assumptions on tillage practices by including different crop management factors affecting water erosion and ultimately soil productivity loss (Sonderegger et al., 2020). Alternative crop management factors were taken from an empirical study conducted in Brazil for a soybean-wheat crop rotation (see Table 4.5) by da Silva et al. (2020).

However, for soil productivity loss, there was also uncertainty related to the model which Sonderegger et al. (2020) used to translate soil erosion to productivity loss which was originally developed by Den Biggelaar et al. (2003). Therefore, I also tested the sensitivity of soil productivity loss to the model's parameter 'conversion factor of water erosion to productivity loss' values of minimum (0.015) and maximum (0.043) compared to the median (0.029) mentioned in Den Biggelaar et al. (2003).

Table 4.5. Overview of crop management factors (source: Da Silva et al. (2020))

Tillage practice	Crop-management factor
Conventional Tillage (Base case)	0.1576
Reduced Tillage	0.0407
No-tillage	0.0407

4.3 Results

4.3.1 Methodological choices

4.3.1.1 Amortisation period of land use change

Regardless of the amortisation period chosen in this analysis, the largest amount of soy-induced transformation of natural land (i.e. classes 50 to 210, see Table 4.2) is found in the Brazilian Amazon followed by the Paraguayan Mata Atlantica (Figure 4.1). However, relative differences between the Amazon and the Paraguayan Mata Atlantica decrease with shorter amortisation periods: one tonne of soy from the Amazon has for an amortisation period of 20 years around 92 % more embedded land transformation than the Mata Atlantica (98 vs 51 m^2/t soy-eq, Figure 4.1.1a) for 10 years amortisation around 12 % more (88 vs 78 m^2/t soy-eq, Figure 4.1.1b) and for 5 years amortisation 7 % more (161 vs 149 m^2/t soy-eq, Figure 4.1.1c). Also, the relative difference between the Amazon and the biome with the least land transformation decreases with shorter amortisation periods: one tonne of soy from the Amazon has, for an amortisation period of 20 years, more than eight times more land transformation than the Espinal (98 vs 11 m^2/t soy-eq; Table S 3.3), for 10 years amortisation more than five times (88 vs 15 m^2/t soy-eq) and for 5 years amortisation also more than five times (161 vs 29 m^2/t soy-eq). However, across most biomes, less forest land cover is converted to soy over the three amortisation periods (Figure 4.1.1). Considering LUC over a 5-year time period compared to a 20-year time period, the share of converted forest decreases in the Amazon from 88 % to 43 % and in the Chaco Seco (Spanish: Dry Chaco) from 80 % to 12 %, but slightly increases in the Paraguayan Mata Atlantica from 25 % to 33 %. In contrast, over the same time-period the share of converted shrubland increases from 6 % to 50 % in the Amazon and from 17 % to 76 % in the Chaco Seco. However, the share of converted grassland does not differ much across the different amortisation periods with for example in the Brazilian Pampa being 80 % for the 20-year time period and 84 % for the 5-year time period.

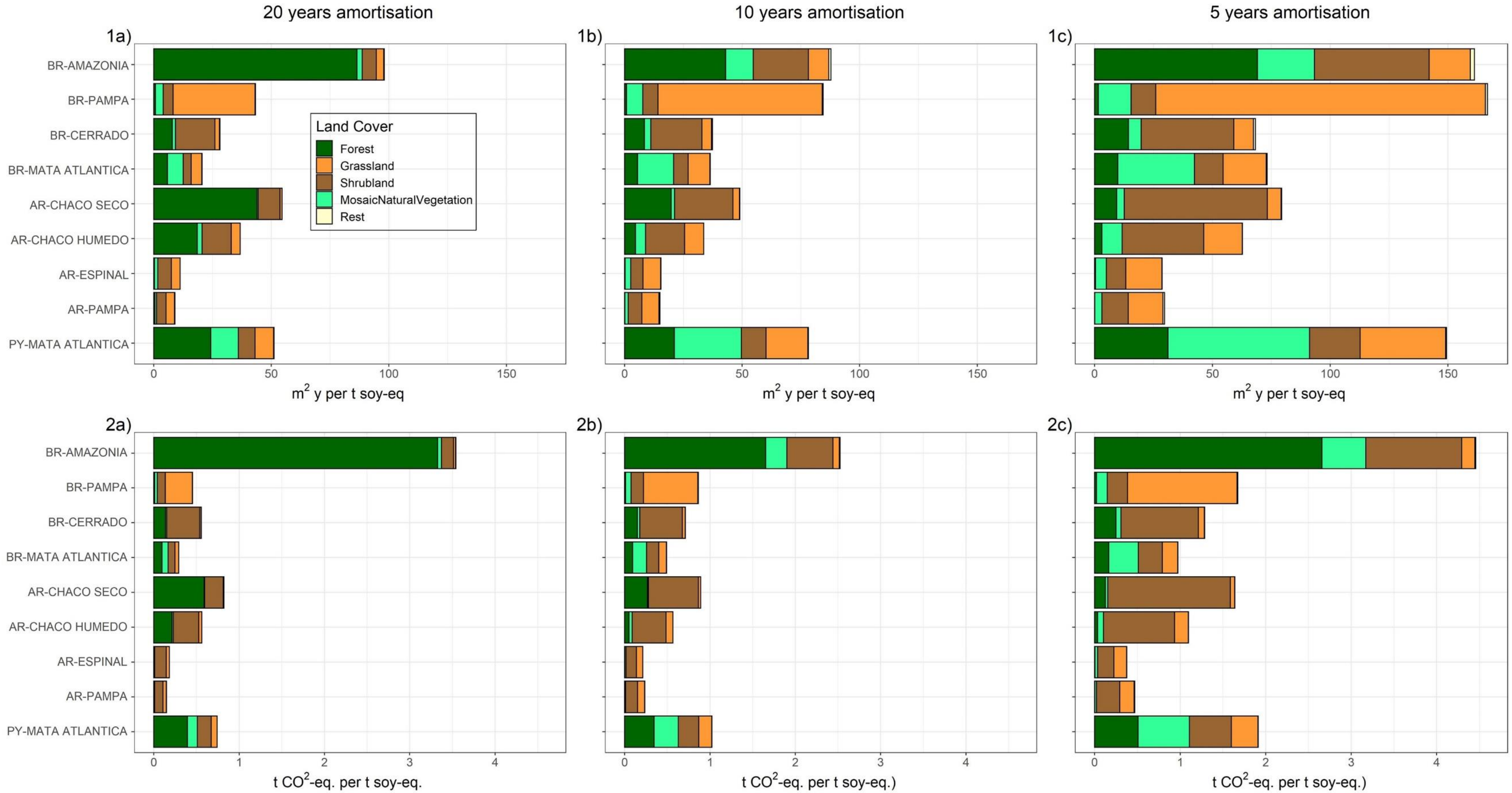

Figure 4.1: Sensitivity to different amortisation time periods: 1996-2016 a), 2006-2016 b) and 2011-2016 c), affecting land transformation of the soy producing biomes in countries 1), as m^2 per soy-eq; and resulting potential LUC emissions 2), as CO_2 per soy-eq. (t t^{-1}). Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. Biomes are ordered within each country by decreasing land conversion area over 20 years allocation.

Considering LUC emissions, forest-biomes (i.e. Amazonia, Mata Atlantica, Chaco Seco and Chaco Humedo (Spanish: Dry Chaco) have the largest LUC emissions considering a 20-year amortisation period (Figure 4.1.2). With a 20-year amortisation period LUC emissions from the Amazon are the largest with 3.54 t CO_2-eq./t soy-eq., followed by the Paraguayan Mata Atlantica (1.03 t CO_2-eq./t soy-eq.) and the Chaco Seco (0.82 t CO_2-eq./t soy-eq.). However, considering a 5-year amortisation period, some non-forest biomes (e.g., Brazilian Pampa) have LUC emissions close to the dry forest Chaco Seco. While the two highest emissions are still linked to the Amazon (4.46 t CO_2-eq./t soy-eq.) and the Paraguayan Mata Atlantica (2.89), non-forest biomes also have considerable emissions with the Brazilian Pampa (2.14 t CO_2-eq./t soy-eq.) and the Cerrado (1.29 t CO_2-eq./t soy-eq.) being comparable to the Argentinian Chaco Seco (1.64 t CO_2-eq./t soy-eq.). Considering a 5-year amortisation time, the Brazilian Pampa has twice as much land converted per tonne of soy (167 m^2/t soy-eq.) compared to the Chaco Seco (79 m^2/t soy-eq.). However, another reason for the low LUC emissions in the Chaco Seco compared to the Amazon, is that forests in the Chaco Seco only store around a third of the aboveground carbon compared to the Amazon (Table S 3.1). While the Pampa does not have a lot of carbon stored in aboveground biomass, most of the carbon emissions of the conversion of the Pampa are due to the soil carbon stocks which are not completely lost after conversion to soy (Esteves et al., 2016).

4.3.1.2 Including land transformation in biodiversity impact

Including transformation impacts in addition to occupation impacts within biodiversity impact assessments makes the relative differences between biomes more pronounced (Figure 4.2c). For example, while occupation impacts for one tonne of soy from the Paraguayan Mata Atlantica are more than six times larger than from the Argentinian Espinal (4.7 vs 0.80 x 10^{-10}/t soy-eq.), including transformation impacts lead to 15 times larger biodiversity impacts for the Paraguayan Mata Atlantica compared to the Espinal (1.69 vs 25.89 x 10^{-10}/t soy-eq.). Biomes with high transformation areas (Table 4.1b) have especially large total biodiversity impacts, namely: Amazon (10.4 x 10^{-10}/t soy-eq.), Chaco Seco (4.5 x 10^{-10}/t soy-eq.) and Paraguayan Mata Atlantica (25.9 x 10^{-10}/t soy-eq.). Including transformation impacts (orange area in Figure 4.2c) in addition to occupation impacts (green in Figure 4.2c) increases total biodiversity damage by between 18.1 % for the Paraguayan Mata Atlantica and 77.4 % for the Chaco Seco. Including transformation impacts also leads to the Pampa in Brazil having a higher total biodiversity damage (5.7 x 10^{-10}/t soy-eq.) than the Brazilian Cerrado (3.1 x 10^{-10}/t soy-eq.). This higher transformation impact is mostly due to the higher transformed area for the Pampa (43 m^2/t soy-eq.) compared to the Cerrado (28 m^2/t soy-eq). Despite the Paraguayan Mata Atlantica and the Chaco Seco having similar land occupation areas

(Figure 4.2a) and land transformation areas (Figure 4.2b), their biodiversity damage is quite different as the CF for occupation is more than four times higher and the CF for transformation more than 15 times higher for the Mata Atlantica compared to the Chaco Seco (see CF in Table S 2.3).

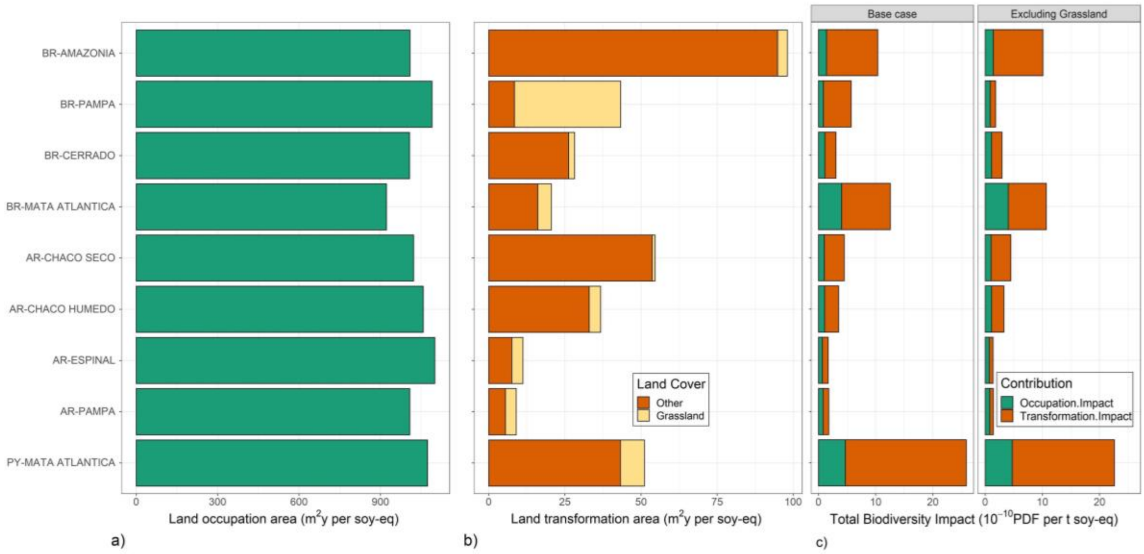

Figure 4.2. Life cycle inventory of land occupation a) and total potential biodiversity damage b) for 1 tonne of soybean produced in 2017. Sensitivity of results to the exclusion of grassland cover to land transformation and resulting biodiversity damage. Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. Biomes are ordered within each country by decreasing land conversion area over 20 years allocation.

4.3.1.3 Land cover classes

Including the land cover type ‘mosaic of agriculture’ (class 30 and 40) in addition to other land cover types (50-210), increases the land transformation (Figure S 3.1.1) and resulting carbon emissions (Figure S 3.1.2) especially for the 5-year amortisation period. Considering a 5-year amortisation period, including the land cover type ‘mosaic of agriculture’, doubles the transformed area for some biomes such as the Brazilian Amazon (161 vs 399 m^2/t soy-eq), Paraguayan Mata Atlantica (149 vs 300 m^2/t soy-eq) and the Argentinian Chaco Seco (79 vs 165 m^2/t soy-eq). In contrast, considering a 20-year amortisation period increases the land transformation only by 18 % in the Brazilian Amazon (98 vs 120 m^2/t soy-eq), 40 % in the Paraguayan Mata Atlantica (51 vs 85 m^2/t soy-eq) and 15 % in the Argentinian Chaco Seco (55 vs 64 m^2/t soy-eq). This increase in land transformation when including mosaic of agriculture leads to an increase in LUC emissions being up to 45 % higher for the case of the Brazilian Mata Atlantica. The land cover mosaic of agriculture is common at the edges of the Amazon (see map in Figure 3.2).

Another ESA CCI land cover class which causes some uncertainty in its application to assess biodiversity impacts is grassland (class 130) as it does not differentiate between natural grassland and pasture (Table 4.2). However, in comparison to pasture, converting natural grassland will lead to larger biodiversity impacts. This would make a particular difference for natural grasslands such as the Brazilian Pampa where I found 80 % of the transformed area to previously be grassland (Figure 4.1.1b). Therefore, if grassland would be excluded from the transformation area, the total biodiversity damage potential would be reduced by about 22 % for the Pampa (1.4 x 10^{-10}/t soy-eq) and then be almost half of the impact of the Cerrado (with 2.9 x 10^{-10}/t soy-eq; Table 4.2c).

4.3.2 Data choices

4.3.2.1 Aboveground forest carbon and double-cropping

Using the alternative data source for forest carbon more than doubles LUC emissions in some states compared to using the dataset for forest carbon from the base case (Figure 4.3). Using the alternative global forest carbon data increased LUC emissions the most in the Argentinian Chaco, such as in the states of Santiago del Estero (203 %), Chaco (152 %) and Salta (140 %), in Paraguay the states of Caazapá (163 %), Caaguazú (164 %) and Canindeyú (145 %) and in Brazil mostly states in the Mata Atlantica such as Parana (106 %), Santa Catarina (104 %) and Sau Paulo (101 %) but also Piaui in the Cerrado (85 %). In contrast, effects of including the alternative double-cropping dataset are less pronounced than including the alternative carbon dataset. Using the alternative global double-cropping dataset instead of the national double-cropping dataset increases LUC emissions most strongly for states in Argentina, such as Buenos Aires (41 %), Santa Fe (40 %) and Chaco (15 %). Outside of Argentina, including the global double cropping dataset increases LUC emissions most strongly in states located in the Cerrado-region of Brazil: Minas Gerais (13 %), Maranhao (12 %) and Tocantins (10 %). A reason for the strong increase of LUC emissions for Argentina could be that the global dataset was based on data from 2000 whereas the national Argentinian data were from 2017 and that in Argentina double-cropping increased most since 2000 compared to Brazil and Paraguay (IBGE, 2018; Ministry of Agriculture, 2017; INBIO, 2017).

An alternative double-cropping dataset and including the land cover type mosaic of agriculture in the land transformation flows has less influence on the LUC emissions than including alternative carbon data or shorter amortisation periods (Figure 4.3). The effect of a 5-year amortisation period is most influential for states with relatively low absolute LUC emissions such as Mato Grosso do Sul (288 %) and Rio Grande do Sul (282 %) in Brazil and Buenos Aires in Argentina (273 %). However, even with those increases, none of these states reaches results of more than 1.5 t CO_2-eq./t soy-eq. The largest absolute LUC emissions using a 5-year amortisation period, are found in the Brazilian Amazon state of Para (5.5 t CO_2-eq./t soy-eq; 55 % higher than results with 20-year amortisation) and Rondônia (3.5 t CO_2-eq./t soy-eq; +39 %) followed by the Brazilian MaToPiBa states with Tocantins (4.81 t CO_2-eq./t soy-eq; +202 %), Piaui (4.5 t CO_2-eq./t soy-eq; +116 %) and Maranhao (3.5 t CO_2-eq./t soy-eq; +110 %). The strongest relative increase of including the land cover type mosaic of agriculture Is found for the states Santa Catarina In Brazil (31 %), Alto Parana (28 %) in Paraguay and Mato Grosso in Brazil (27 %).

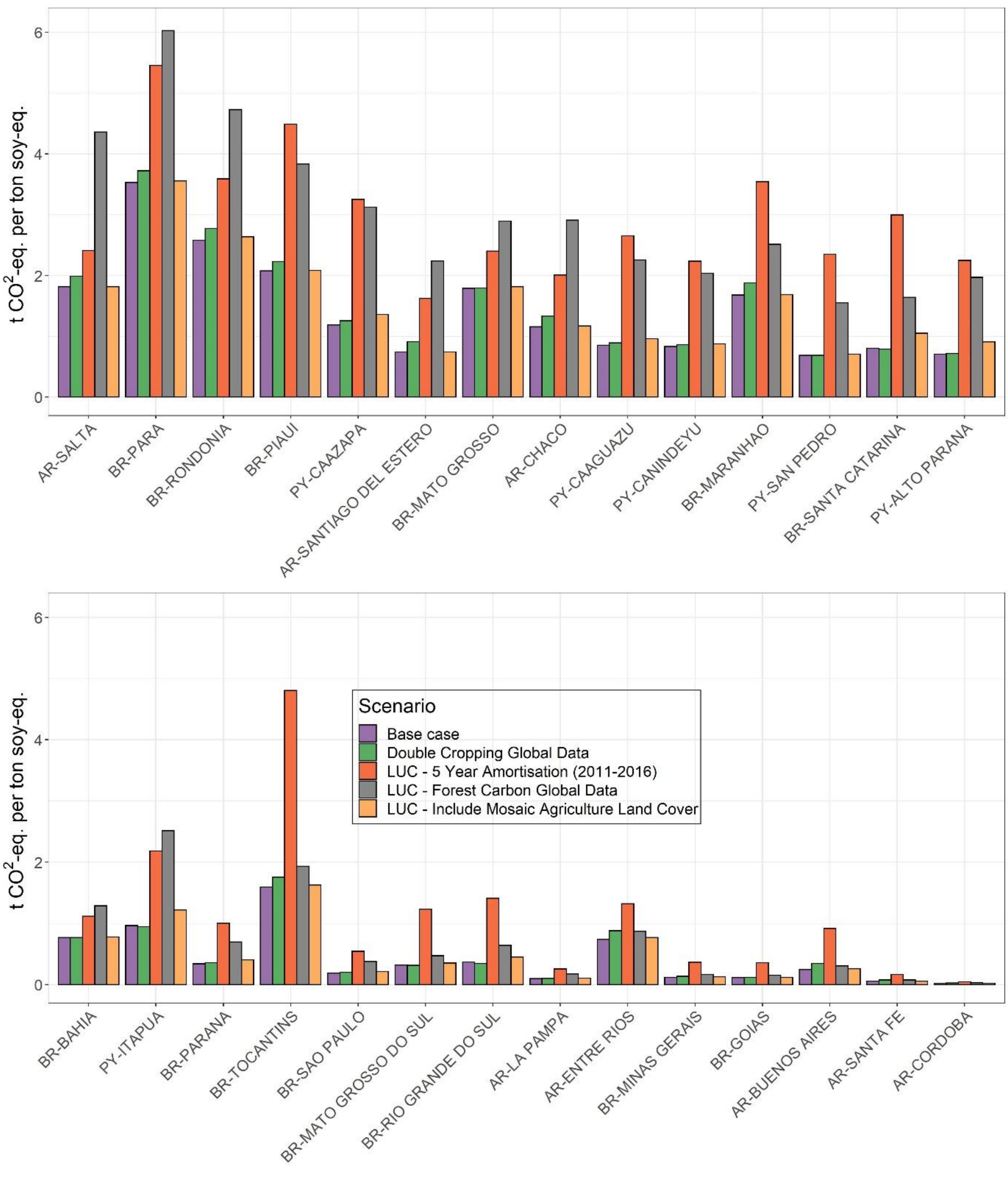

Figure 4.3. Sensitivity of soy-induced land use change emissions to methodological choices and global data sources instead of national data compared to the base case (i.e. 20-year amortisation (1996-2016); national double-cropping data and spatially-explicit carbon dataset), as CO_2 per soy-eq. ($t\ t^{-1}$). Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. States are ordered by decreasing deforestation area embodied in produced soybeans with states having most embedded deforestation area at the top and those with least deforestation area at the bottom right left of the graph (aggregated from municipality-level results by weighting with the commodity mix)

4.3.2.2 Water scarcity: temporal variability

Water scarcity footprints of some states are quite sensitive to the monthly variability in characterization factors (Figure 4.4). Using maximum monthly values for the growing season of soybeans (November to June), doubles the water scarcity footprints for some states in north-eastern and north-western Brazil, namely Bahia (+120 %), Rondônia (+105 %) and Minas Gerais (+101 %) compared to water scarcity footprints estimated with yearly mean CFs. However, of these three states a high absolute water scarcity is calculated only for Bahia (370 m^3/tonne soy eq.), whereas yearly mean water scarcity footprints for Rondônia (154 m^3/tonne soy-eq.) and Minas Gerais (187 m^3/tonne soy eq.) are lower. Even the water footprint estimated with monthly maximum values for Rondônia is lower than around half of the state's yearly mean water scarcity footprint. In contrast, states which have water scarcity footprints sensitive to monthly minimum values are mainly in the north east of Brazil such as Para (-85 %), Maranhao (-74 %), Piaui (-73 %) and Tocantins (-72 %). However, of these states only one state has high yearly mean water scarcity, namely Piaui (1030 m^3/tonne soy eq.) whereas the other states have medium yearly mean water scarcities values ranging between 163 m^3/tonne soy-eq. (Para) to 187 m^3/tonne soy (Tocantins). However, there are also states where using monthly minimum and maximum values affects the water scarcity footprint minimally. For example, states in southern Brazil such as Sao Paulo (8-12 %) and Parana (9-12 %), northern Argentina such as Chaco (12-14 %) and Salta (14-19 %) and south-east of Paraguay such as Alto Parana (8-12 %) and Itapúa (10-17 %). This observed lack of variability within the growing season is likely due to the different climate in those states. Whereas the north-east of Brazil is known to be semiarid as it is in a rain shadow region, the south of Brazil, east of Paraguay and north of Argentina are in less warm climates and experience less seasonality in precipitation (Carrão, Naumann and Barbosa, 2016).

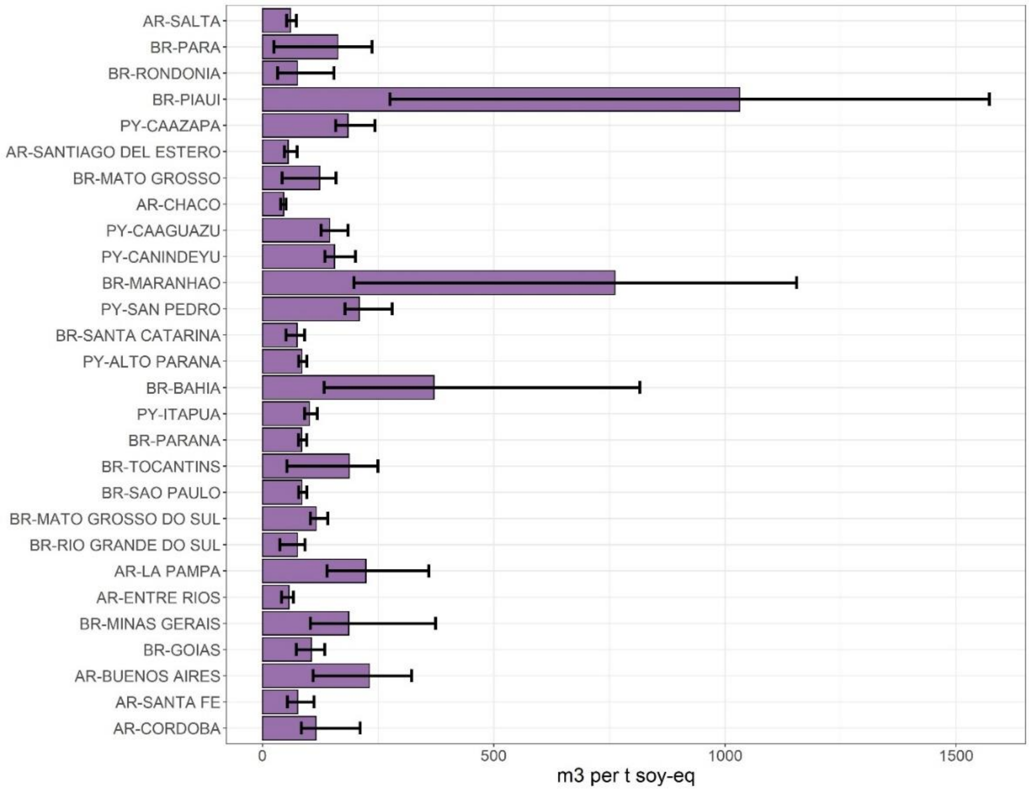

Figure 4.4. Water scarcity footprint for one tonne of soybean produced in different states in 2017. Error bars illustrate the monthly minimum and maximum water scarcity within the soybean growing season (November-June). Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. States are ordered by decreasing land conversion area over 20 years allocation excluding Mosaic of agriculture land cover type.

4.3.3 Uncertainty in the Inventory and LCIA

Soil productivity loss is more strongly influenced by the geographic location of the soy production state than the farmer's tillage practices or uncertainties in the soil productivity loss model. The use of the minimum value for soil productivity loss from water erosion reduces productivity loss only by around 48 % (Figure 4.5).Though alternative tillage practices such as reduced tillage lowered soil productivity loss by 74 % and no-tillage even by 77 % (percentage reduction is the same for each state as the alternative parameters for tillage and maximum and minimum model values are not spatially-explicit). However, in the case of the southern Brazilian state of Santa Catarina, even using minimum soil erosion values for no-tillage and minimum model values for soil productivity loss (i.e. best case) leads to a soil productivity loss of 3.2 % over the coming 50 years (Figure S 3.2) being higher than the maximum value for seven other states estimated by assuming regular tillage practices and maximum soil productivity loss model values (i.e. worst case). These states showing low soil productivity loss are all located in Argentina characterised by relatively low precipitation leading to less intense water erosion. Assuming conventional tillage and maximum soil production loss (i.e. worst case), soil productivity loss is estimated to be low for the high soy producing states such as Santa Fe (0.77 %), Buenos Aires (0.95 %), and Cordoba (1.55 %). It is worth noting that two of the three states currently producing the largest amounts of soybeans (i.e. more than 15 million tonnes of soy in 2017) across the three producing countries, are experiencing comparatively high levels of soil productivity loss, namely Rio Grande do Sul (5.0 % to 14.4%) and Parana (3.4 % to 14.4 %) in Brazil (range depending on the tillage practice). Compared to these two high soy-producing states, only Santa Catarina in Brazil experiences higher soil productivity loss (6.2 % to 26.7 %).

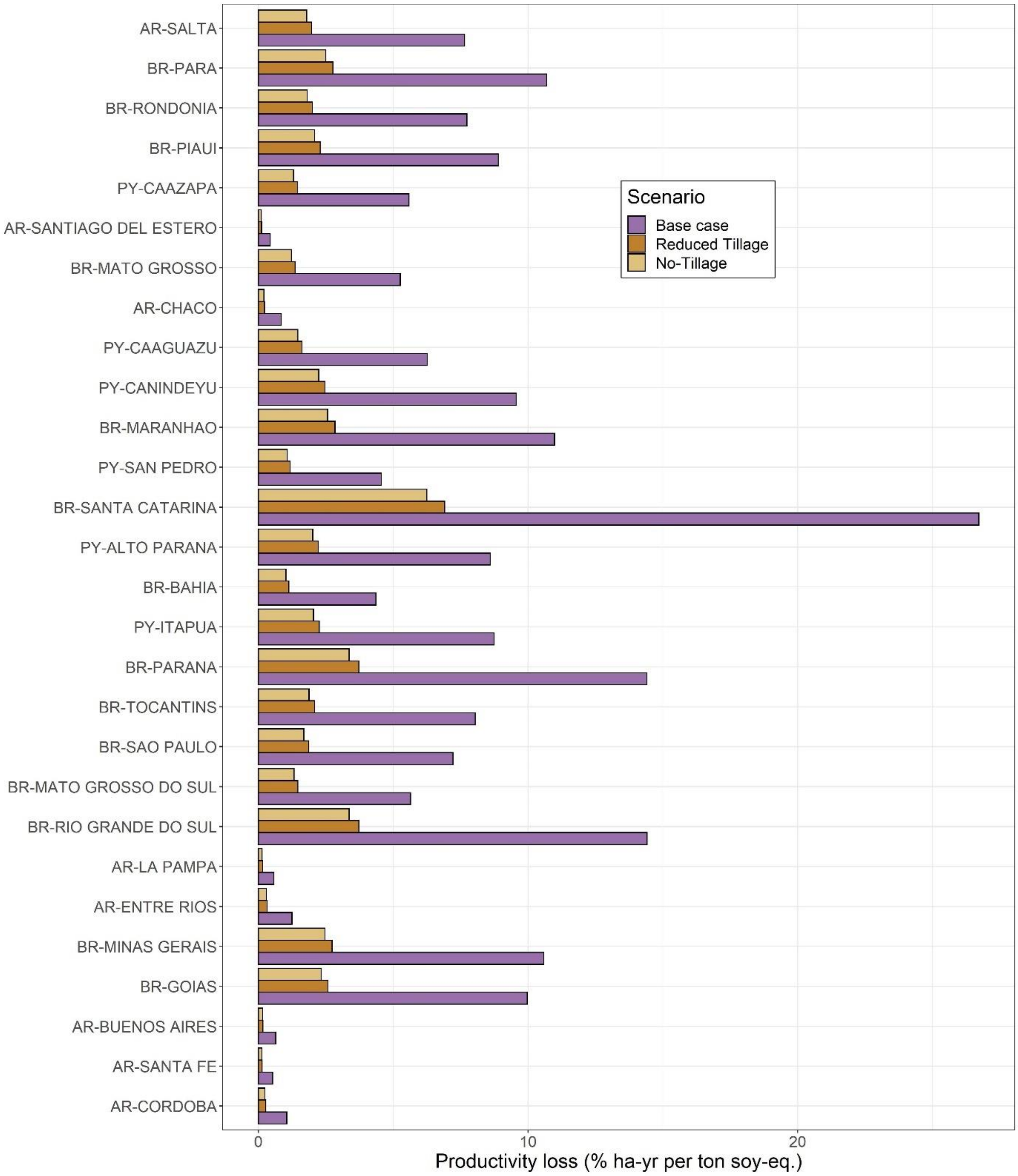

Figure 4.5. Soil productivity loss due to water erosion depending on tillage practice for one tonne of soybean produced in 2017. Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. States are ordered within each country by decreasing land conversion area over 20 years allocation excluding Mosaic of agriculture land cover type.

4.3.4 Comparison of LUC emission estimates to other similar studies

LCA estimates of LUC carbon footprints can differ considerably depending on the employed land cover dataset to estimate LUC and included natural vegetation types to calculate carbon stock changes in the conversion to cropland. For example, in Escobar et al. (2020) for soy-induced LUC emissions for Mato Grosso the median value across municipalities is 0.12 t CO_2-eq./t soy-eq which is much smaller than the median value of 2.5 t CO_2-eq./t soy-eq estimated in this chapter (Figure 4.6, variability in each state in Figure S 3.3). The latter was based on including all natural vegetation types in the conversion using the ESA CCI (2017) land cover dataset, whereas Escobar et al. (2020) only included emissions from forest conversion using the Brazilian PRODES dataset. While this chapter had a wider geographic scope covering all major soy producing countries in Latin America, this required the use of a land cover dataset such as ESA CCI with coarser spatial resolution and not differentiating between natural forest loss (e.g. fire, logging) and forest conversion to cropland like PRODES (Numata et al., 2011). However, differences in LUC carbon footprint estimates between this chapter and Escobar et al. (2020)'s for the MaToPiBa region are less pronounced. For instance, the average value for LUC emissions estimated in this chapter is only slightly higher than Escobar et al. (2020)'s for Piaui (4.5 vs 3.4 t CO_2-eq./t soy-eq), Maranhao (3.2 vs 1.2 t CO_2-eq./t soy-eq) and Bahia (1.0 vs 1.0 t CO_2-eq./t soy-eq). The differences in LUC emission estimates in this study compared to Escobar et al. (2020) are likely mostly due to differences in forest land cover detection between PRODES and ESA CCI. Using ESA CCI detects 15 times more forest conversion for soy compared to using PRODES in the Amazon (11.61 % vs 0.76 % of harvested soybean area) using the same soybean raster from Song et al. (2021) and a five-year LUC amortisation period (PRODES estimates based on own calculations based on Trase data). In contrast, in the Cerrado the share of soy-induced forest conversion was much more similar between ESA CCI and PRODES (2.52 % vs. 2.46 % of harvested soybean area). Nevertheless estimates of forest loss in Latin America with ESA CCI are comparable to those estimated with the Hansen et al. (2013) dataset according to Li et al. (2018) which also does not differentiate between natural forest loss and anthropogenic forest loss (Harris et al., 2021).

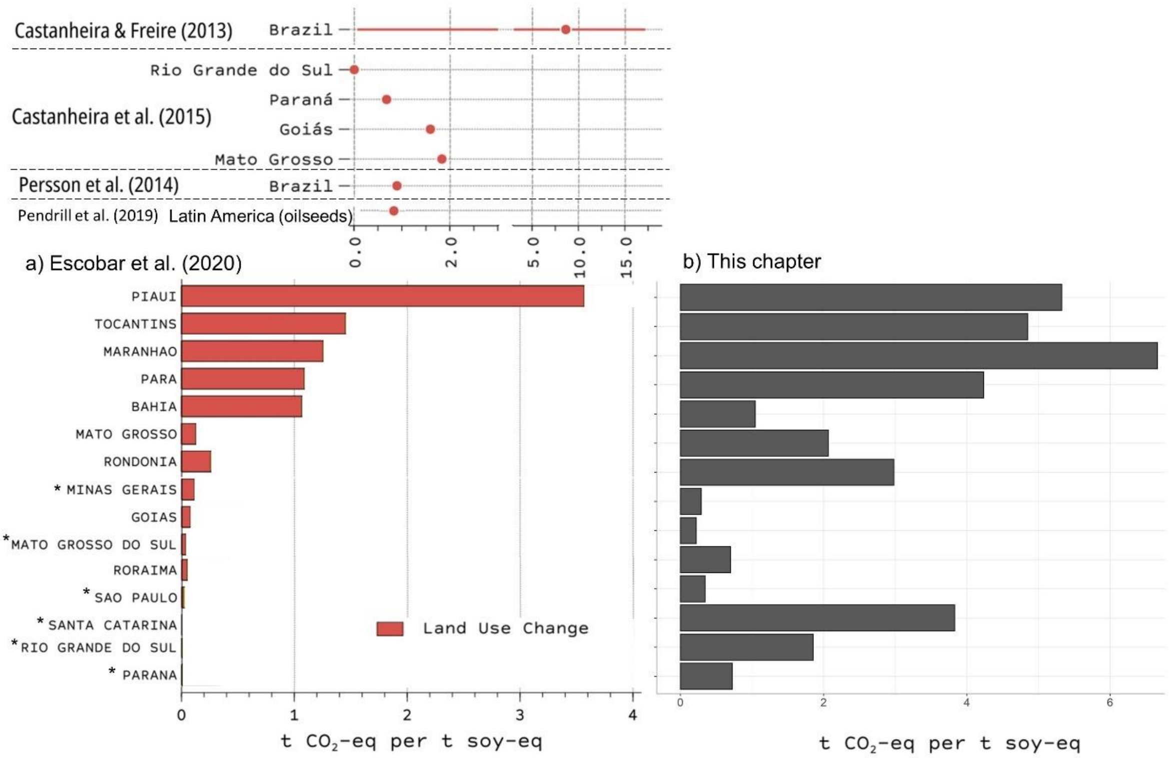

Figure 4.6. Greenhouse gas emissions from LUC of Brazilian soy at the level of states and country in related studies using a Life Cycle Assessment approach (adapted from Escobar et al. 2020) (a) and results compared from this chapter using a five-year amortisation period (b). Asterisks indicate states in which no or only partial LUC emissions were quantified in Escobar et al. (2020) because the PRODES land cover map only covers the Amazon and the Cerrado but not the southern states of Brazil. Note the different x-axes.

4.3.5 Application to the supply chain of the EU

4.3.5.1 Land use change emissions

When applying some of the results of this sensitivity analysis to the EU supply chain, by using Trase supply chain mapping data, the EU's LUC carbon footprint was increased by using a 5-year amortisation period, including mosaic of agriculture in the land conversion as well as using a non-spatially-explicit forest carbon dataset (Figure 4.7). Compared to the 'base case', choosing a 5-year amortisation period almost doubled LUC carbon footprint (0.73 vs. 1.38 t CO_2-eq./t soy-eq.), whereas selecting a 5 year amortisation period and additionally including the land cover type mosaic of agriculture in the land transformation more than tripled the LUC carbon footprint (0.73 vs 2.47 t CO_2-eq./t soy-eq.). Additionally, using the non-spatially-explicit forest carbon data also almost doubled the LUC carbon footprint compared to the base case (0.73 vs. 1.31 t CO_2-eq./t soy-eq.).

Taking different methodological choices and choosing alternative data in the estimation of soy-induced LUC emissions, leads to less geographically concentrated states contributing to the EU's LUC carbon footprint compared to estimates in the base case (Figure S 3.4). While Mato Grosso produced 15 % of the EU's imported soybeans (Figure S 3.4a) and contributed 40 % of the LUC emissions in the base case, this was reduced to 28 % for an amortisation period of five years. Considering LUC emissions with a 5-year amortisation period, 13 states are responsible for 80 % of the impact, whereas in the base case only 10 states are responsible for 80 % of the impact. However, among these states the share they contribute to these 80 % LUC emissions is influenced by the amortisation period. In the base case the second largest contributing state is Para in the Amazon (8 % of LUC emissions) and the third largest Bahia in the Cerrado (6 % of LUC emissions). In contrast, with a 5-year amortisation the second largest is Rio Grande do Sul (8 % of LUC emissions) and the third largest Parana (7 % of LUC emissions) which are both in the Mata Atlantica biome. It is also worth noting that the LUC emissions of Paraguay, with a 5-year amortisation period, are 17 % of the EU's total soy LUC emissions from these three producing countries, whereas this share was only 11 % in the base case.

However, differences in results are more pronounced at the municipality scale compared to the state scale (Figure S 3.4). For an amortisation period of 20 years (base case) only around half as many municipalities contribute to 60 % of the LUC emissions compared to calculating impacts with a 5-year amortisation period (24 vs 39 municipalities in 2017). While using a 20-year amortisation period most of these are located in the Brazilian Amazon (except two municipalities in the MaToPiBa region), considering a 5-year amortisation period also highlights municipalities in Argentina (i.e. La Paz, Villaguay and Moreno) and more in the MaToPiBa region (i.e. Balsas in Maranhao, Santa Filomena in Piaui and Formosa do Rio Preto in Bahia) and Paraguay (i.e. Alto Parana) are being identified as contributing to the 80 % of LUC emissions.

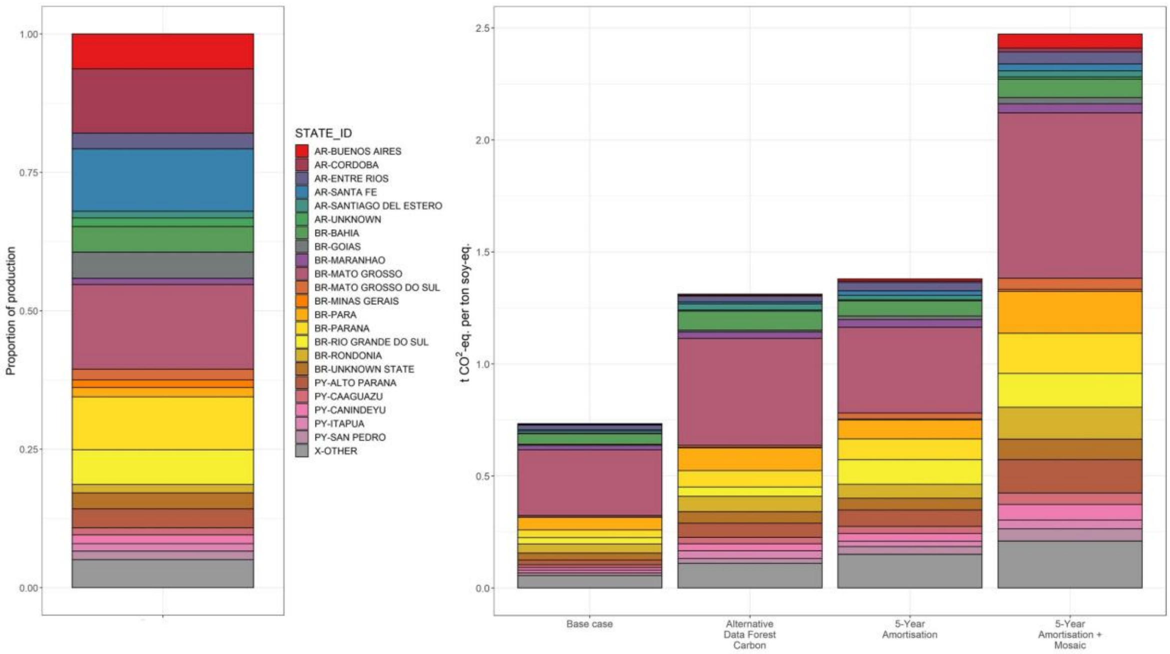

Figure 4.7. Comparison of soy-induced LUC emissions for the EU depending on different sensitivity choices. Each bar illustrates the proportion of the total LUC emissions related to soybean production of each state within the three producing countries Brazil (BR), Argentina (AR) and Paraguay (PY).

4.3.5.2 Biodiversity impacts

Including impacts from land use change (transformation impact) in addition to impacts from land use (occupation impact) in the EU's biodiversity impact leads to a 60 % increase (15.5 vs 9.7 10^{-10} PDF; Figure 4.8) compared to the base case. However, this was increased only by 51 % (14.7 vs 9.7 10^{-10} PDF) if conversion of the grassland land cover was excluded from the transformed area. Considering the relative contribution to the total impacts, the three states contributing most to the biodiversity impact remained the same: Parana, Mato Grosso and Rio Grande do Sul which are all in Brazil. However, the relative contribution changed: while Mato Grosso contributed 20.3 % to the occupation impact, this state contributed only 15.0 % to the total biodiversity impact (Figure S 3.5).

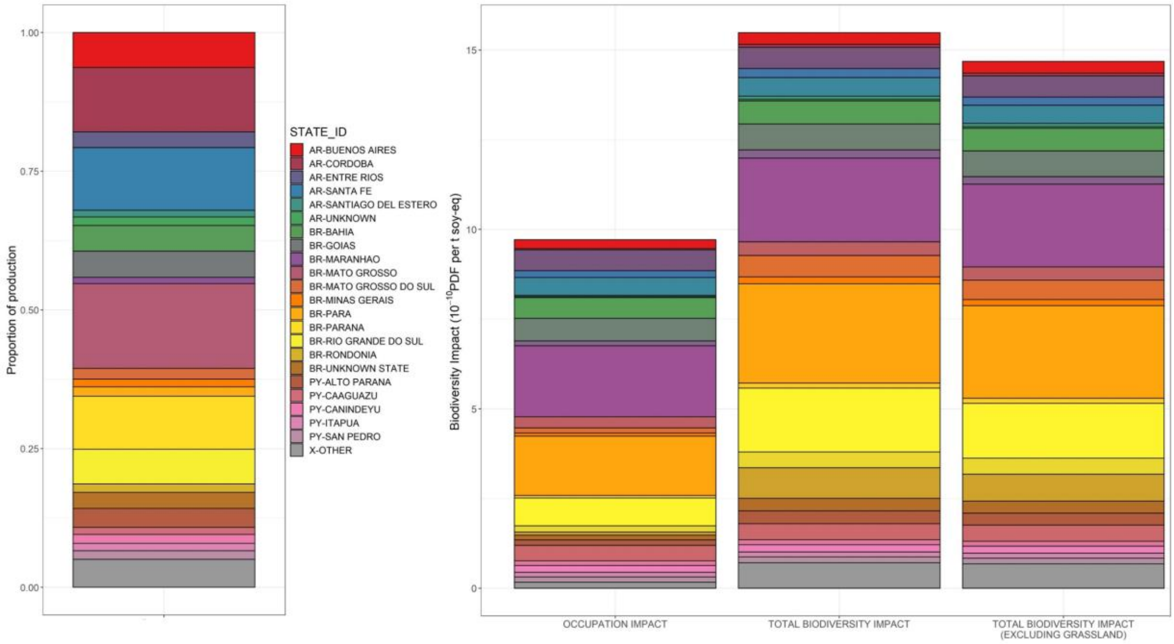

Figure 4.8. Comparison of Occupation impact (base case) and sensitivity to including transformation impacts in Total Biodiversity Impact for the EU as well as excluding grassland within amount of transformed area per tonne soy.

4.4 Discussion

LCA is a decision-support tool identifying key impacts along the entire value chain of products and therefore improvement strategies (Hellweg and Milà I Canals, 2014). However, there is a large variability and uncertainty in product's agricultural environmental impacts due to a large extent from land use change (Poore and Nemecek, 2018). Uncertainty in land use change emissions embedded in agricultural commodities is due to the often unknown origin of production (Lam et al., 2021), hindering accounting for the spatial variability in land use change emissions (Escobar et al., 2020), but also due to different modelling and data choices (Garofalo et al., 2022). This uncertainty hinders providing simple science-based guidance about which life cycle stages or geographies are hotspots of environmental impacts (Liao et al., 2020). While spatial heterogeneity is considered a crucial source of this uncertainty (Patouillard et al., 2018), it is not well understood how this compares relatively to other sources of uncertainty such as methodological choices, data sources or assumptions on farming practices. Considering the urgent need for reliable LCA estimates to guide the transition towards a sustainable food system, more knowledge is needed about the underlying reasons for the large variability and uncertainty in the impact assessment of agricultural products. To my knowledge this is the first study trying to quantify the influence of different aspects contributing to the uncertainty of a commodity's agricultural impacts from water and land use as well as land use change across multiple producing countries comparing spatial heterogeneity, methodological and data choices but also assumptions on farming practices. I found in this chapter that impacts of land use and land use change can be more sensitive to methodological choices and assumptions on farming practices than the differences that arise due to the spatial location of the land use.

However, the importance of these factors depends on the geographic location of the producing region and the studied impact category. The choice of the amortisation period (methodological choice) and an alternative forest carbon source (data choice) influenced the LUC emissions strongest, which was most pronounced in the Brazilian Amazon. In contrast, excluding grassland from the amount of transformed area (methodological choice) and including transformation impacts was most influential for biodiversity impacts particularly in the Brazilian Pampa biome. Assumptions on soil tillage practices (uncertainty in inventory data) were most affecting soil productivity loss, strongest influenced in southern Brazil.

In the following section, I first compare my findings to those of other existing studies. In addition, I will discuss methodological choices such as the land use change amortisation period, the quantification of the amount of transformed area and the representativeness of different data sources varying in spatial and temporal detail. Finally, I will reflect on the implications of these findings for policy and future research.

4.4.1 Methodological choices

4.4.1.1 Amortisation period

Besides the variability due to different land cover maps, LUC emissions of South American soybeans are highly sensitive to methodological choices such as the amortisation period. A shorter amortisation period highlights regions with more recent expansion. For example, in using a 5-year amortisation period (i.e. using land cover maps of 2011) compared to a 20-year amortisation period (i.e. using land cover maps of 1996) resulted in a stronger increase of the LUC emissions for states in Paraguay and the MaToPiBa region in Brazil compared to states in the Brazilian Amazon or Argentinian Chaco. Whereas LUC emissions quadrupled in Piaui, tripled in Tocantins and doubled in Maranhao, states in the Brazilian Amazon (e.g. Para, Rondônia, Mato Grosso) and Argentinian Chaco (e.g. Salta) only saw relative increases between 30 and 50 %. In Paraguay many states tripled their LUC emissions with a 5-year amortisation period compared to a 20-year amortisation period (e.g. Caazapá, Caaguazú, Alto Parana). The regional differences in the sensitivity to the amortisation period are likely because the Soy Moratorium was introduced in 2008 in the Amazon which then displaced LUC to the neighbouring Cerrado (Gibbs et al., 2015). Similar policies were introduced in Argentina with the Federal Forest law and in Paraguay the 'Zero Deforestation law' in 2004, though with varying regional effectiveness due to a lack of enforcement (Nolte et al., 2017). The 20-year time period is a more conservative approach to allocate LUC emissions and follows the PAS2050-1 methodology (BSI PAS, 2012) and the EU Renewable Energy Directive (EU, 2009). Longer amortisation periods also include land transitions to intermediate land uses such as pastures before being ultimately converted to soybeans. Within Latin America it is often the case that natural land is first converted to pastures before ultimately several years later being converted to more profitable cropland (Carvalho et al., 2019). Having longer timeframes to allocate LUC incorporates transition of grassland to soybeans which was a critique of short time-frames (Brandão et al., 2021). However, the choice of amortisation period is highly debated and referred to as 'arbitrary' by some (e.g. Brandão et al., 2021; Schmidt et al., 2015; Persson, Henders and Cederberg, 2014).

4.4.1.2 Land cover classes

To analyse land use change, there are also a range of different land cover datasets available differing in geographic coverage, spatial resolution, land cover classifications and temporal periods covered. I chose in this chapter the ESA CCI (2017) dataset to consistently cover (over more than two decades) the three largest soy producing countries in South America. However, estimated LUC emissions here differed for the Brazilian Amazon compared to values reported in Escobar et al. (2020) who used national PRODES land cover maps. Global land cover datasets have a higher error in differentiating land cover classes than national datasets (Pérez-Hoyos et al., 2017). There are several reasons for the lower accuracy of global land cover datasets compared to national datasets: the first being that global land cover datasets have a lower spatial resolution than national land cover maps with ESA CCI being 300 x 300 m while PRODES has 30 x 30 m resolution (Nunes et al., 2019). Secondly, national datasets (such as the Brazilian MapBiomas) often include more land cover classes than global datasets, for example differentiating between primary and secondary forest, grassland and pasture and savannah and forest (Souza et al., 2020). Therefore, national land cover datasets refined to the national context aligned to national policy definitions of 'forest loss' might be more suitable for studies aiming to inform national policies such as the Brazilian Forest Code which only aims to reduce primary forest loss (e.g. Soterroni et al., 2018). However, these fine-resolution land cover datasets are limited in their geographical coverage to a few biomes or countries and in their temporal coverage often hindering time-series analyses or monitoring of annual land cover change (Hansen et al., 2008). Therefore, to support global policies aiming to reduce land use change, reliable land cover datasets are needed as well (Zioti et al., 2022). Satellite remote sensing is developing rapidly improving the spatial resolution and differentiation into vegetation types (Buchhorn et al., 2020). However, for users of these global land cover maps, it is a challenge to identify how reliable these land cover datasets are for different geographic regions and purposes and how they might differ to national land cover datasets.

4.4.2 Data choices

A challenge in the application of methods to quantify impacts of water and land use (change) more broadly, is that data are not available in all parts of the world and for all vegetation types with the same detail. While a lot of research exists on forests and Brazilian land use change emissions, less is known about other vegetation types and producing countries. Given the EU's ambition to lead in reducing deforestation and their high share of soy imports from Argentina and Paraguay, differences in the quality of the data between producing countries used to support land use change policies, could lead to sub-optimal outcomes. For example, using carbon density datasets underestimating carbon storage in Argentinian dry forests (Baumann et al., 2017) might lead to policy prioritizing protection of Brazilian tropical moist forests at the detriment of forest conversion in Argentina. For example, the GEOCARBON dataset (Santoro et al., 2021) used in this chapter estimated that the average forest in Argentina has less than 40 % of the biomass compared to the reported average value for Argentina in the global FAO Forest Resources Assessment, whereas for Brazil this difference was less than 10 % (FAO FRA, 2010). A possible reason for the differences between biomass density estimates conducted in late 2010s reported in Santoro et al. (2020) compared to those based on estimates in the 2000s published in FAO FRA (2010), could be the increasing fragmentation of forests in the last twenty years (Montibeller et al., 2020; Frate et al., 2015). While spatially-explicit biomass or carbon data are available for forests, these are missing for other natural vegetation classes such as shrubland which I found in this chapter to account for the majority of converted land cover in the Chaco (choosing a 5-year amortisation). However, it is challenging to know, in regions and for vegetation types lacking detailed data, to what extent the impacts of land use and land use change are over- or underestimated.

4.4.3 Implications for policy and practice

4.4.3.1 Challenges and opportunities of sensitivity of results for decision-making

LCA is used by companies and public sector actors to understand the impact of land and water use in their agricultural supply chains. Incorporating data tracing the spatial origin of agricultural land use into LCA, helps understanding of the current location-dependent impacts of commodities (Kulak et al., 2018). This knowledge can inform supply chain sourcing, product design and farming practices. The spatially-explicit LUC emissions footprints of soybean production allow supply chain actors and policymakers to identify geographic hotspots to improve landscape planning and sourcing decisions (Lam et al., 2021). Within product design for example, the choice of ingredients can help to mitigate greenhouse gas emissions by considering each ingredient's emissions depending on the sourcing region and associated land use change (see Liao et al., 2020). As LUC emissions can be the largest contributor to an ingredient's carbon emissions, reducing the uncertainty of LUC emissions is crucial for a robust estimation of carbon emissions of different alternative ingredients within a product's recipe (Liao et al., 2020). While the increasing amount of spatial detail improves the accuracy of water and land use impacts, understanding the uncertainty inherent in these novel data can be challenging (Kulak et al., 2018). However, given the large contribution of land use change to the GHG emissions of agricultural commodities (Poore and Nemecek, 2018) and commitments of corporations and governments to reduce deforestation (Lambin et al., 2018) robust estimates to monitor progress and evidence benefits of deforestation commitments are crucial. For example here, using the spatially-explicit forest carbon dataset more than halved the LUC emissions from the EU's imported soybean in 2017 ascribing smaller impacts to Paraguayan and Argentinian states (Figure 4.6). Therefore, whilst footprinting methods are useful to identify current hotspots, researchers need to be careful in the communication of findings about their research objectives and make clearer what the implications of their choices are on the results and which decisions they are therefore most suitable to inform. Given that the choice of data and methods can have fundamental impacts on the conclusions, it would be advisable for LCA practitioners to clearly communicate the fact that – for example in this study – shorter amortisation periods will highlight regions linked to higher recent deforestation and that choosing land cover data with supra-national coverage likely increases the uncertainty of results compared to national data. At present it remains a challenge for decision-makers to navigate and interpret this complex information.

Out of a realization that voluntary actions of few private actors was not enough to reduce deforestation rates meaningfully at scale, consuming country governments have realized the need to introduce a law banning companies from importing commodities produced on recently deforested land (EC, 2020e). Ambitious policy currently developed in this context includes the EU's Proposal for a regulation on deforestation-free products that would exclude the import of products such as soy, beef, palm oil and wood produced on recently deforested land (EC, 2021b). A challenge to support with available data is that in the EU's proposal 'deforestation' is defined as the conversion of forests to agricultural production therefore excluding natural loss (e.g. fires) or conversion to plantation forest. However, neither the Hansen et al. (2013) dataset nor the ESA CCI maps, two global datasets, differentiate between natural and anthropogenic forest loss. This study showed the effect these different definitions can have in the identification of geographic hotspots of soy-induced forest loss. As ESA CCI identifies any forest loss, it overestimated especially in the Amazon soy-induced forest loss compared to values reported with PRODES (see Escobar et al., 2020) which only identifies primary forest conversion to cropland. However, national-specific land cover datasets such as PRODES which is only available for the Brazilian Amazon and the Cerrado (Souza et al., 2020) are limited in their ability to be used to monitor a regulation on deforestation-free products which is global in scope (EC, 2021b). As this chapter showed that for EU imports almost as much soy is from Argentina and Paraguay together than from Brazil, agreement is needed about for which purposes national and for which purposes global land cover maps should be used. Therefore, to implement and monitor compliance to trade agreements and initiatives (e.g., EU proposal for a regulation on deforestation-free products, EU Mercosur, REDD+ (Reducing Emissions from Deforestation and forest Degradation), more alignment in definitions such as 'forest' and 'deforestation' and supporting datasets of forest land use/cover maps are needed. This would also facilitate comparison between different studies.

While efforts to protect forests will benefit meeting climate targets, the sole focus on carbon-rich ecosystems should not overlook potential trade-offs with other sustainability goals such as biodiversity loss. For example, to date, the scope of the EU's Proposal for a regulation on deforestation-free products is limited to forests (it uses the FAO definition of forests as >10 % tree coverage) excluding threatened wetlands, grasslands or shrublands (EU Greens/European Free Alliance, 2022). Therefore, NGOs suggested to include other threatened ecosystems besides forests (Greenpeace, 2022). However, to monitor compliance of no-conversion of those valuable ecosystems (e.g. grasslands, savannahs, wetlands), there is currently a gap of available land cover datasets. The ESA CCI maps used in this study were limited for biodiversity impact assessment by their lack of differentiation between natural grassland and pasture. Therefore, land cover datasets need to be developed which can not only monitor the impact of trade on deforestation but also loss of other ecosystems

4.4.3.2 LUC amortisation period

As LUC emissions are highly sensitive to the length of the amortisation period, more dialogue between policy-makers and researchers is needed so that policy-makers understand the consequences of these methodological choices. This would help to find consensus, align methods and provide guidance to researchers about which amortisation period should be used for which research objectives. The British Standard Institution (BSI PAS, 2012) specified in 2008 a 20-year amortisation period as the standard within LCA which is used since (e.g. Brandão et al., 2021; Liao et al., 2020). However, there is no scientific justification for this ‘arbitrary’ 20-year period (Flynn et al., 2012). Therefore, and given the high sensitivity of results to this amortisation period, Persson et al. (2014) have argued that the length of the amortisation period should be decided in the political context. However, a challenge at the moment is that a multitude of ‘cut-off’ dates exist for deforestation depending on biome (e.g. 2008 for Amazon Soy Moratorium; Gibbs et al., 2015), states (e.g. 2008 for Salta in Argentina; Vallejos et al., 2021), certification standard (e.g. 2005 for High Carbon Value clearing for RSPO, 2017) or international trade agreement (e.g. EU Proposal for a regulation on deforestation-free products: 31 December 2020; EC, 2021b). Newig et al. (2020) have identified the inconsistency in policies as a major challenge to govern global telecoupled sustainability challenges. Schmidt et al. (2015) argued against short amortisation periods as the consequence is that LUC is overestimated at the agricultural frontier whereas indirect LUC on the existing agricultural land is ignored. Indirect land use change is a land use change in one location which is caused by land use change in another location (Meyfroidt et al., 2018). For example, increases in soybean demand can increase land prices thereby causing cattle pasture expansion into the Brazilian Amazon. Therefore, longer amortisation periods account for some of these complex land conversion dynamics in South America where intermediate use as pastures is common whereas the actual socio-economic driver of deforestation is often soybean production (Le Polain de Waroux et al., 2019). However, estimating indirect land use change is even more subject to scientific debate than direct LUC (Persson et al. 2014). Therefore, rather than adopting a general long amortisation period (such as 20 years) for any producing country and any commodity, principles could be developed to specify the amortisation period depending on the political context of traded commodity, producing country or sector (e.g. food, biofuels, fashion).

4.4.4 Future research: data comparison, consensus-building, amortisation

This chapter has demonstrated that methodological choices and alternative data sources can have large implications on the regions identified as key contributors to commodities' water, land use and land use change impacts. As this study is restricted to one region and commodity more research is needed comparing how different methodological and data choices affect the results for other commodities and producing regions. This will be important as the implications of these results have wide-ranging consequences for decision making linked to supply chains of globally traded agricultural products and their sustainability. Advances in novel spatial data have allowed an improvement in the reliability and representativity of environmental impacts (Patouillard et al., 2018), however selecting the most appropriate data remains a challenge. Recently many global maps of land cover (e.g. ESA CCI, 2017, Copernicus Global Land Service developed by Buchhorn et al. (2020), Hansen et al., 2013), carbon density (e.g. Santoro et al., 2021; Zarin et al., 2016) and farming practices (Waha et al., 2020) have been developed. However, understanding is incomplete as to how the choice of spatial data varying in geographic or temporal coverage affects the measured impacts of location-specific agricultural production and the conclusions for supply chain environmental impact assessment.

While using data with global coverage benefits comparability between studies, these datasets might not be representative for every geographic context. For example, in this chapter, I found forest carbon density using global GEOCARBON (Santoro et al., 2021) to be comparable for Brazil however, it was less than half for Argentina compared to values reported in the UN Global Forest Resources (2010). Therefore, more research is needed on better understanding the differences between national data and global data across different geographic regions. A promising solution in this direction might be the platform which Zioti et al. (2022) developed which aims to improve the integration and harmonization of different land cover maps for Brazil including both national and global maps. However, a more standardized approach might be needed to compare and harmonise across wider geographic regions to understand for which purposes regional or national data are needed and for which global datasets are sufficient. For example, for national policies such as the Brazilian Soy Moratorium national land cover products such as Mapbiomas might be more suitable (Garofalo et al., 2022). In contrast, for policies such as the EU proposal for a regulation on deforestation-free products global datasets applicable across tropical producing country will be needed. However, a remaining challenge is understanding how these different land cover products differ and how these differences would translate into varied land use change emission estimates.

4.5 Conclusions

In this chapter, I have attempted to test the sensitivity of different choices in the implementation of LCA on impacts of land and water use associated with imported soy from South America. I found that besides the spatial and temporal resolution of underlying data and indicators, methodological choices and assumptions can be just as influential on estimated impacts. Depending on the choice of included land cover types and amortisation period, the land use change carbon intensity can triple for a soybean importer. Additionally I found differences in identified regions of geographic hotspots of LUC emissions using a global compared national land cover map such as by Escobar et al (2020). However, the sensitivity to alternative data was dependent on the region: water scarcity impacts were only influenced by the temporal resolution of the indicator in regions with seasonal climate, and biodiversity impacts were only sensitive to the inclusion of grassland in the transformed area in some natural grassland biomes (e.g. Brazilian Pampa). In contrast, uncertainty in soil productivity loss is largely due to a complete lack of data on farmer’s tillage practices. Therefore, this research has contributed to the existing field of assessment of trade-driven global environmental change by highlighting the need for more research to compare how differences in data and indicators varying in geographic coverage, spatial and temporal resolution affect estimates of environmental impacts.

Given the supra-national scale of this study, the findings can be applied to inform multi-national companies and international trade agreements to identify geographic hotspots. However, this chapter also illustrated the need to agree within a political dialogue on normative choices such as the time period to allocate land use change emissions among commodities, territories and actors when designing international environmental policies such as sustainable trade agreements (e.g. EU Mercosur), zero deforestation agreements (e.g. EU proposal for a regulation on deforestation-free products) or payments for ecosystem services (REDD+). Moreover research would benefit from working closer with policy-makers, so that policy-makers can understand the implications of their own choices such as definitions chosen (e.g. of ‘forest loss’ or ‘forest’), but also so that policies are designed based on the latest science and the latest available data to support monitoring of compliance to policies and avoid burden shifting to other sustainability challenges. More coherence is needed in the use of definitions and data to support governance of global telecoupled sustainability challenges. However, development of a more coherent approach requires firstly understanding differences between available data differing in geographic coverage (global vs national/local), spatial granularity and temporal coverage. Secondly more dialogue between academia and stakeholders in NGOs, multi-national companies and producing as well as importing governments is needed to find agreement on methods to measure progress towards common targets.

Chapter 5 Future Scenario Analysis

Sub-national land use change of future international demand for agri-commodities: In-depth assessment of the linkage of GLOBIOM with Trase for Argentina

Abstract

Tropical forests have the potential to mitigate climate change through the storage of carbon in their biomass. Increasingly companies and countries recognise this potential as one of the solutions to meet the Paris climate goal. A driver of tropical deforestation is consumption of agri-commodities. Considering stakeholder requirements, there is a need to understand how the projected global demand on agri-commodities might affect future global land use change. Most of the models supporting these types of research questions combine global-scale dynamic land use models with downscaling approaches finding relationships between drivers and observed sub-national land use change patterns to project future land use change. Additionally, a lot of research exists on tropical moist forests, little is known about land use pressures in tropical dry forests, such as the Chaco in Argentina. Therefore, this chapter aims to contribute to this body of research via developing understanding of how sub-national (rather than national) supply chain mapping data as well as local-specific data (rather than global), would change the spatial pattern of projected land use change from the 'Global Biosphere Management Model' model. In an exploratory analysis, I found that compared to the default DownScale calibration, including additional sub-national supply chain mapping – and local – data lead to greater spatial concentration of the cropland expansion at the detriment of forest in few grid cells in the northeast of the Chaco. I conclude that including spatially-explicit supply chain and local data can improve the understanding of where within a country land use change is likely to happen in future. This would allow the focusing of efforts to reduce detrimental environmental impacts. However, I also describe how more research is still needed to improve the robustness of these early findings.

5.1 Introduction

In the last two decades, agricultural expansion driven by global demand for commodities has become a major driver of the destruction of natural ecosystems in tropical and subtropical regions (Pendrill et al. 2019a). This is releasing large amounts of greenhouse gas emissions into the atmosphere contributing to the acceleration of climate change and the loss of biodiversity (Harris et al., 2012). Especially the demand from European countries and growing populations scarce in land resources such as China is driving detrimental land use change in producing countries such as Brazil, Indonesia and Argentina (Baumann et al., 2017). Therefore, commitments have been established such as the Amsterdam Declaration in Europe or the UN New York Declaration on Forests that aim to halt deforestation linked to imported products. It is argued that to understand implications of future consumption and trade strategies on food security, biodiversity and climate mitigation, a systems-based approach is needed that links both the supply (i.e. production) and the demand side (i.e. consumption) (West et al., 2014). As places of production are often distant from places of consumption, a global scale approach is needed (Sun, Tong and Liu, 2017). However, at the same time, land-based solutions to global sustainability challenges are highly localized and context-specific (depending on factors such as investment, infrastructure availability and agricultural productivity) while supply chains are complex.

Therefore, to guide strategies about land-based solutions towards global sustainable development, models are needed which on the one hand have the global scale but also the fine resolution to take into account differences in local characteristics. One example of a model which tries to achieve this is the dynamic partial equilibrium model 'Global Biosphere Management Model' (GLOBIOM) (Havlík et al., 2011) which depicts future land use patterns and trade pathways. To improve the robustness of these kind of models, the observed land use change needs to be calibrated with highly spatially refined data (Krisztin and Wögerer, 2021; Leclère et al., 2016). To test the benefit of including more spatially-refined data for the calibration, I chose Argentina as a case study as whilst a lot of research exists on tropical moist forests and Brazil, tropical dry forests such as the Chaco in Argentina have received less attention (Baumann et al., 2017). Recently, novel data mapping sub-national trade flows have become available (developed by Trase; www.trase.earth), linking producing regions to consuming countries. This allowed me in this study to evaluate which consuming countries are likely contributing most to future land conversion in the Chaco based on my model projections and the Trase data on market share by department.

Argentina has become an important global producer and exporter of products like soybeans, sugarcane and cattle (FAOSTAT, 2021). Soybeans are the most valuable export product for Argentina and around 90 % of Argentinean soybeans are exported worldwide (OECD, 2021), making it dependent on world market prices. The production increases were possible through improvements in both yield and expansion of planted area (FAO, 2017). In recent years, a further increase of export taxes in 2008 seems to have negatively affected export volumes by hindering investment in agriculture (FAO, 2017). Argentina has compared to its competitors Brazil and USA, higher commercialization costs such as for transportation, storage and export taxes despite having a competitive advantage in terms of production (Giancola et al., 2009). World market prices will increase as global demand for agricultural commodities is increasing, driven by increases in population and wealth (Alexandratos and Bruinsma, 2012). However, it is not clear how changes in commercialization costs or increases in soybean demand will affect production and cropland expansion in future in Argentina.

Deforestation accelerated in Argentina since the 2000s with a peak in 2008 (Vallejos et al., 2015) which was driven largely (46 %) by pastures for cattle raising and to a lesser extent (33 %) by soybean production (Pendrill et al. 2019a). In 2014, deforestation contributed 14.5 % to Argentina's greenhouse gas emissions (FAO, 2019). Within Argentina, most deforestation takes place in the Chaco ecoregion which has become one of the frontier regions of cropland expansion in Latin America (Hansen et al., 2013). Within the Chaco, the provinces Salta and Santiago del Estero are two of the top 14 jurisdictions of high deforestation in Latin America directly driven by the conversion to soybean (Song et al., 2021). However, since 2013 deforestation rates have decreased by 60 % in Argentina (Hansen et al., 2013). This decline can be partly explained by a 50 % reduction of world market soybean prices between 2012 and 2016 (Sly, 2017; see Figure 5.1), increases in export taxes of the Argentinean government and the introduction of a federal forest law in 2007 (Nolte et al., 2017). However, due to limited enforcement, the success of the Argentinean forest law to reduce deforestation is debated (Sly, 2017) and restricted to few jurisdictions (Nolte et al., 2017). As land use change emissions depend on the carbon-density of the converted land, especially for countries mostly covered by non-forest habitat like Argentina, a sub-national approach is needed accounting for heterogeneity of carbon-density of converted land.

Figure 5.1. Change in soybean world market prices (Source: Indexmundi, 2022)

In the Argentinian Chaco land use change seems to be mostly driven by an increase in global soybean demand (Fehlenberg et al., 2017), whereas in other Argentinian regions other drivers seem to be relatively more important. While global companies commit to zero-deforestation policies, production and land conversion is conducted by local and regional actors which can move their expansion activities depending on legal land use constraints (Meyfroidt et al., 2018). To understand the134ork134ut of local land use policies on actors' investment decisions into new land, Le Polain de Waroux et al. (2016) interviewed more than 80 of these agricultural companies active in the 'Gran Chaco' in South America. These authors used a nested logit model to analyse determinants of land investments. Le Polain de Waroux et al. (2016) found that variables explaining the probability for investment in land were proximity to current investment of companies and availability of cheap forest land; less strong was low deforestation regulations and low enforcement (Le Polain de Waroux et al., 2016). Here, positively correlated but not significant were high yields and land prices (Le Polain de Waroux et al., 2016). The variable which was not significant in Le Polain de Waroux et al. (2016)'s study was transport costs. In the Amazon in Brazil, factors reducing deforestation rates were the enforcement of the Brazilian Forest Code, interventions in soybean and cattle supply chains, restrictions to access to credit and protected area expansion (Nepstad et al., 2014; Arima et al., 2014). Le Polain de Waroux et al. (2018) argued that frontier expansion depends on change in accessibility (e.g. road building), environmental conditions, technology, producer prices and/or demand, subsidies or other policies.

Bearing the results of these initial studies in mind, I was therefore interested in the following research questions:

1.) Will some new variables derived from the spatially explicit supply chain data from Trase correlate with the observed land use change in Argentina?

2.) How will these updated and new variables change the spatial patterns of the land use change projections?

To respond to these questions, we re-calibrate the DownScale model used to downscale the global land use change projections from the GLOBIOM model, to test the effect of incorporating TRASE and local data. GLOBIOM is a global dynamic bottom-up partial equilibrium model projecting future land use change (Havlík et al., 2011) at the scale of 30 regions, one of them being Argentina as a country. Sofar the default DownScale model was based on variables explaining biophysical characteristics (e.g. mean temperature, altitude, soil characteristics) and socio-economic factors (e.g. distance to market, wood harvest cost, total population). However, other possible factors explaining land use change such as distance to export market, crop-specific harvested area and local biophysical data were missing. In this approach, the allocation of future land use change within Argentina depends on the interplay between future agricultural demand, biophysical characteristics, distance to the first logistic hub in the supply chain and distance to ports. This allowed me, through re-calibration of the DownScale model, to explicitly account for the relationship between land use change and the spatial distribution of different end-market specific soybean supply chains in Argentina based on my model projections and the TRASE dataset for market share by department and distance to logistic hub.

5.2 Methods

5.2.1 DownScale model

The potential to improve the allocation of land use change by including spatially-explicit supply chain information was explored using the DownScale model (Krisztin and Wögerer, 2021; Leclère et al., 2016) which links to IIASA’s GLOBIOM model (Valin et al., 2013; Havlík et al., 2011). The DownScale model aims to allocate to a higher spatial resolution the land use change projected by GLOBIOM, using as much as possible observed high-resolution data (Krisztin and Wögerer, 2021).

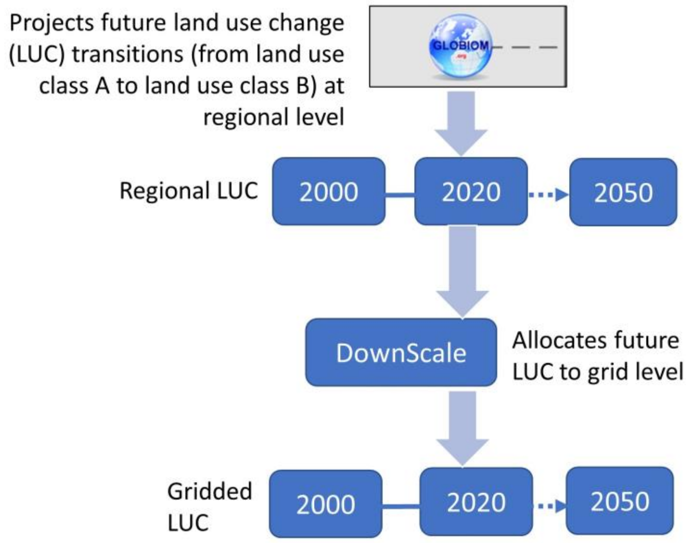

Figure 5.2. Description of how the land use change transitions projected from GLOBIOM are connected to the DownScale Model to generate high-resolution land use change projections.

Future land use and land use change is affected by changes in global demand (e.g., due to increases in population and consumption) and supply (e.g., depending on biophysical characteristics affecting agricultural productivity) connected through international trade. These relationships can be modelled with the global economic model GLOBIOM (Havlik et al., 2013). GLOBIOM is a global bottom-up partial equilibrium model focusing on the main sectors relevant for land use (i.e. forestry, agriculture and bioenergy). It models demand, bilateral trade and market equilibrium at the level of 30 different world regions (as in supra-national) whereas agricultural production is modelled at the grid cell level (Leclère et al., 2014). Competition between different land uses (i.e. cropland, pasture, forestry) in each pixel are determined by maximizing the consumer and producer surpluses (Valin et al., 2013). GLOBIOM resolves, recursively, global land use competition between different land use sectors in 10-year time steps starting in 2000 until 2050 depending on constraints in resources and technology (Figure 5.2). Here, land use change model outputs from GLOBIOM were taken for the scale of Argentina. To further refine these land use change projections from the national scale to the grid scale, the GLOBIOM outputs were further downscaled. In contrast to GLOBIOM where the calibration of the land use change projections is based on national scale data (from FAOSTAT), the DownScale model can be run with data only available for Argentina and with much higher spatial resolution representing local characteristics. The DownScale model is spatially-refined with Simulation Units (grids) of 5 x 5 arcminutes which results in 6488 pixels for Argentina which is equivalent to around 10 x 10 km at the equator (Leclère et al., 2016). Data were aggregated to the different major soybean producing biomes in Argentina: Chaco, Humid Pampas and Espinal (Figure 5.3).

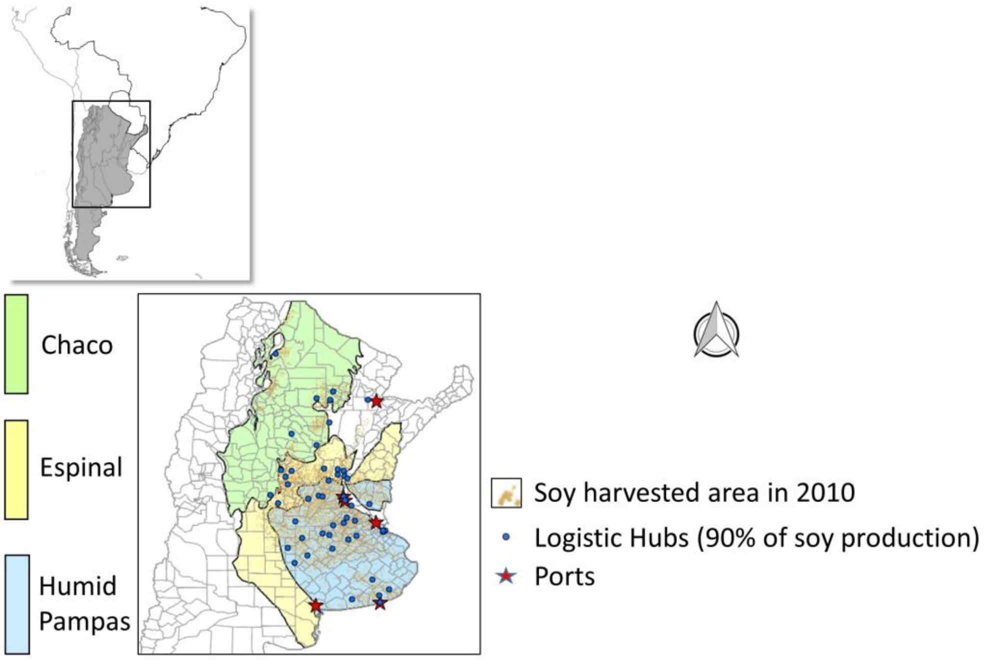

Figure 5.3. Study area by biome in Argentina with borders of provinces in grey and locations of major ports illustrated through red stars and of crushing facilities in blue circles (98 % of soybean export). Biome boundaries are from TNC (2019); province boundaries from DIVA-GIS (2019); soy harvested area from Song et al. (2021); locations of ports and logistic hubs from Trase. More on data in Table 5.2.

5.2.2 Prior module variables setup

Within the DownScale model, the prior module (see Figure 5.4) consists of an econometric model estimating which drivers are explaining the observed land use change pattern. These drivers are either static (not changing over time) such as geophysical variables (e.g., slope, soil, altitude) or dynamic (changing over time) such as GDP, population and land rent. Based on this information the prior module estimates the probability of land use change for each Simulation Unit. The prior module will select from all the provided drivers (explanatory variables; left box in Figure 5.4) those which correlate with the observed land use change (dependant variable; top box in Figure 5.4). The choice of drivers is based on economic theory of land use where the likelihood of land use change depends on the relative profitability of the land use and the cost of conversion (e.g., see Nerlove, 1979).

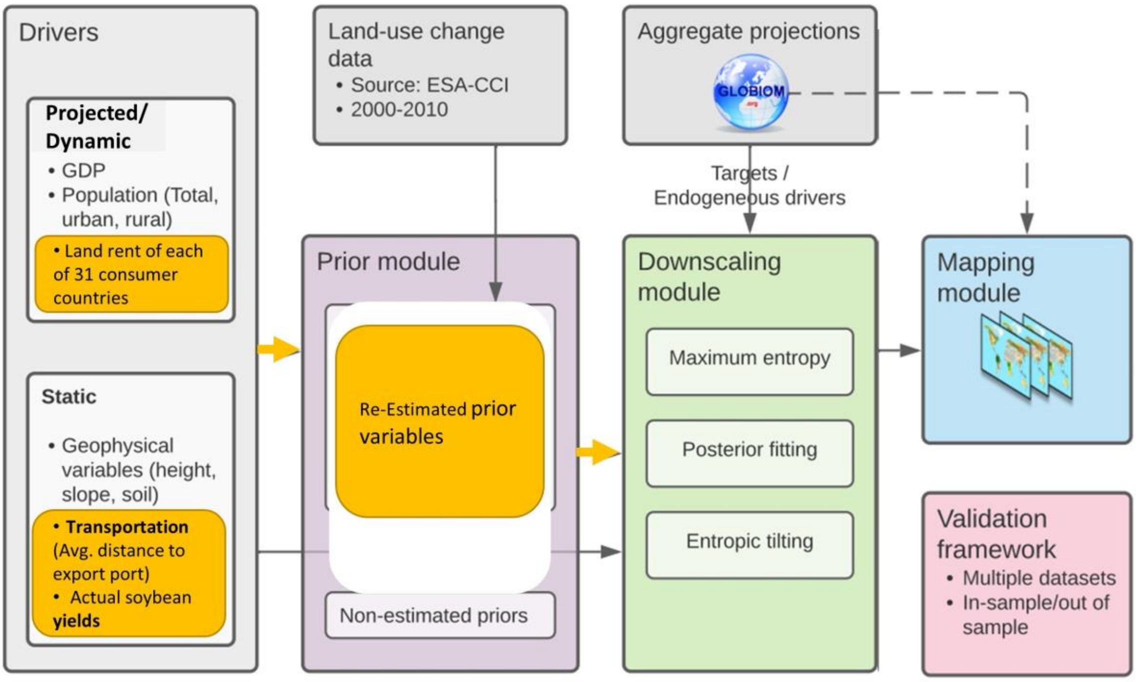

Figure 5.4. Overview of the DownScale model. Arrows indicate the flow of data. In yellow are the data taken from Trase (adapted from Krisztin and Wögerer, 2021)

To test how the output of the DownScale model would change by using local high spatial resolution as input variables (drivers) for the prior module compared to global low spatial resolution (green rows in Table 5.1), the prior model was run additionally. These were conducted with a) Argentina-specific spatially-resolved input variables mostly providing information about biophysical characteristics and transport deemed relevant by representatives of the Argentinian government (red rows in Table 5.1) and b) spatially-resolved input variables derived from Trase providing information about economic aspects (yellow rows in Table 5.1). The prior module is using stochastic search variable selection based on a Bayesian approaches to choose which of the input variables are correlating with observed land use change (Krisztin et al., 2015).

Here, to test the effect of different types of drivers, the prior model was run with four different variable set-ups: default version including variables with coarse spatial resolution (D), default together with the TRASE-variables with higher sub-national resolution (T; see yellow boxes in Figure 5.4 and yellow rows in Table 5.1), default together with variables from the project ‘SPIPA’ (Strategic Partnerships for the Implementation of the Paris Agreement) (S) which refers to relevant data provided by the Argentinian government; as well as default variables combined together with both TRASE and SPIPA variables I. For each variable included in each variable set-up the correlation with the observed land cover change (from 2000 to 2010 with ESA CCI (2017)) was quantified by the prior module to be either positive, negative or no correlation. It should be noted that this correlation does not imply significance or causation (Rohrer, 2018).

Projections of future changes in different land cover classes aggregated to the national scale were taken from the GLOBIOM model and fed into the Downscaling module (see Figure 5.4 and more details in section 5.2.4). Land use classes in GLOBIOM are cropland, grassland, managed forest, plantation forest, primary forest and natural land. However, the prior module only estimated priors describing the likelihood of conversion from one land use to another land use for the following changes:

- From unmanaged or managed forest to Grassland and Cropland;
- From Grassland to Cropland;
- From other natural land to Grassland and Cropland and reversion back.

For the modelling, I adopted the following assumptions: Supply chain patterns will be constant over time and; using only soybeans is representative for the observed spatial pattern of general cropland expansion as soybeans are one of the major drivers of cropland expansion in Argentina Pendrill et al. (2019a).

Table 5.1: Updated and new prior module drivers which were all aggregated to Simulation Unit. Rows with variables set-up in red are those from the default (D), in yellow those from TRASE (T) and in green those from SPIPA (S). Columns D, T, S and C specify the variables incorporated in each prior module variable set-up.

Type	Variable	Description	Source	D	T	S	C
Transportation	Mean time to Market (min)	Gridded travel time for goods to closest market	Uchida and Nelson (2009)	X	X	X	X
Transportation	Travel distance to first logistic hub OR port (km) Travel distance to first port in supply chain (km)	Gridded travel distance of soy producing municipalities to hub in supply chain [km]	Data source developed by Trase (based on Open Street Map)		X		X
Transportation	Distance to roads Distance to village	Distance to roads in 2014 Distance to next local village	SPIPA			X	X
Land rent	Forest yield Wood harvest cost Pasture yield	Harvested wood yield (tons) Wood harvest cost (USD) Harvested grass yield (tons)	G4M (Spatially explicit forest management model) at IIASA	X	X	X	X
Land rent	Soybean yield Market Share	Gridded soybean yield in 2017 (tons) Gridded Market share for each GLOBIOM region (US Dollar)	Data source developed by Trase (based on MoA, 2020). Data source developed by Trase (based on freight on board from customs data)		X		X
Land-use	Harvested Soybean area in 2001, 2010 and 2020	Soybean harvested area share in grid cell	Data source used by Trase (originally from Song et al., 2021)		X		X

Type	Variable	Description	Source	D	T	S	C
Biophysical	Mean temperature, Mean precipitation, Altitude, Slope, Soil type	Mean within pixel of temperature, precipitation, altitude (m) and slope (in degrees) as well as dominant soil type	Skalský et al. (2008)	X	X	X	X
Biophysical	National Park coverage, Moisture balance Distance to rivers Altitude Evapotranspiration, native forest and managed by law coverage, annual precipitation, effective soil depth, provinces	 Distance to rivers and ponds Altitude from digital elevation model (dem)	SPIPA			X	X
Socio-economic	Total population, Rural population		Jones and O'Neill (2016)	X	X	X	X

5.2.3 Data sources and processing

To update existing drivers or test improvement of variables, I used multiple different data sources (Figure 5.3, Table 5.2).

Table 5.2. Overview of data sources

Data sources	Resolution	Time period	Source
Soybean yield	Department	2016-2018	Data source developed by Trase (based on MoA, 2020).
Soybean harvested area	30 x 30 m	2001, 2010, 2020	Data source used by Trase (originally from Song et al., 2021)
Price	Shipment	2016-2018	Data source developed by Trase (based on freight on board from customs data)
Flow of soybeans to importing country	Department	2016-2018	Spatially explicit model on Production to Consumption (SEI-PCS; Godar et al., 2015); data on Trase platform
Distance to port	Department	2016-2018	Data source developed by Trase (based on Open Street Map)

Soybean harvested area

We derived Argentinean data on harvested soybean area in 2001 (first available year), 2010 and 2020 using the dataset of the Global Land Analysis and Discovery (GLAD) laboratory (Song et al., 2021). While the GLAD dataset is available yearly at 30 x 30 m resolution, I aggregated these to the simulation grid unit as percentage of harvested soybean area as this is the finest shared resolution at which the variables for the model of land use change are available.

Soybean yield

Yearly average soybean yield data for each department were used from Trase. To generate these data, Trase mainly used the data available from the Ministry of Agroindustry Argentina (MoA, 2020). As for some departments the data were missing, yields were approximated by Trase (2020) using department-specific soybean production data from MoA (2020) together with Song et al. (2021)'s harvested area maps. For this chapter, I have used the soybean production data as freely available from the Trase.earth platform. This dataset was aggregated as yield [tonne/ha] to the simulation grid unit.

Soybean price

Prices of exported soybean were derived from the Freight on Board (FOB) financial values on Trase which are based on customs data and specific for each export market (Trase, 2020). As this dataset did not include prices for the domestic market, I took the price of 274.75 US Dollar per tonne soybean for 2017 from TESEO (2021).

Distance to Logistic Hub

I estimated distances between soybean producing department and first logistic hub in the supply chain using intermediate outputs calculated for Trase. The first logistic hub was in the case of crushed soybeans a silo or crushing facility and in the case of uncrushed soybeans a port. Trase estimated the distances to logistic hub by minimizing the distance between supply node (i.e. producing department) and demand node (i.e. logistic hub or domestic consumption hub) using the road network available from OpenStreetMap.org. It has to be noted that this dataset included only distances from the middle of the producing department to the middle of the logistic hub department, not accounting for distances within these departments. As each department supplies more than one logistic hub, in this study I have calculated a weighted average distance depending on percentage soybean tonnage flowing through each logistic hub for each exporting market. For departments which are not yet producing soybeans, I have calculated the distance as distance to the closest trade hub of which each market is already sourcing from. For 144ork144ulturts which are already producing soybeans but not yet for a certain export market, I have included as distance a high value (i.e. 1000 kilometre). This was done to artificially decrease the likelihood of sourcing from this department as I assumed a static supply chain in this study. The resulting dataset was aggregated as distance [km] to the simulation grid unit for each export market.

Distance to Port

To test sensitivity to choosing a different node along the supply chain to calculate the distance from producing municipality to, I have calculated the 'distance to port' in addition to the 'distance to logistic hub'. Distances between soybean producing department and exporting port were calculated using intermediate outputs calculated for Trase [internal data]. Trase linked ports specific to each export market with producing departments based on a variety of sources such as national trading and customs data, optimizing by travel distance. If better information was unavailable, Trase followed the methodology of the Spatially Explicit Information on Production to Consumption Systems (SEI PCS) model published in Godar et al. (2015) available on Trase (see Trase, 2020 for more details). I took the distance between each producing department to department of port from internal Trase data which were based on the shortest distance of the trade network from OpenStreetMap.org. Again, it has to be noted that this dataset included only distances from the middle of the producing department to the middle of the port department, not accounting for the specific location of the port within these departments. As some departments supply more than one port, in this study I have calculated a weighted average distance depending on percentage soybean tonnage flowing through each port for each exporting market. For departments which are not yet producing soybeans, I have calculated the distance as distance to the closest port of which each export market is already sourcing from. This dataset was aggregated as distance [km] to the simulation grid unit for each export market.

Soybean tonnage flow

We used the flows of soybean tonnage produced in each department and exported to each consuming market from (Trase, 2020; methodology is published in Godar et al., 2015). While the Argentinean Trase dataset is available yearly between 2016 and 2018 for more than 90 different countries, I have aggregated these to the 30 different economic regions (i.e. supra-national) included in the GLOBIOM model (e.g., 'EU Mid West') as this is the smallest geographic unit the model works in. As the publicly available data from Trase did not include domestic consumption within Argentina, I have used a TRASE-internal dataset which was developed as part of the SEI PCS model.

5.2.4 Scenarios for future projections

To explore the potential consequences of future changes in demand for food and feed as well as trade on land use change in Argentina, I used a scenario based on the Shared Socioeconomic Pathway (SSP): SSP3 'Regional Rivalry' (Popp et al., 2017). SSP3 would be described by hardly regulated land use change, reduced trade flows and a resource-intensive consumption (Popp et al., 2017). In the GLOBIOM model, the SSP3 scenario translates into a 51 % increase in Argentinean population between 2000 and 2050, and a 68 % increase in the yield of oil crops over the same period [Calculations based on GLOBIOM output shared by David Leclère]. This scenario corresponded to historical climate mitigation efforts (Representative Concentration Pathways Reference (RCPRef) and SPA0 (Shared Climate Policy Assumptions, see Kriegler et al., 2014).

For all prior model runs, net total land cover change for each land cover category at the scale of Argentina projected from 2010 to 2050 was taken from GLOBIOM (see Figure 5.4) and is the following: cropland increases by 2.6 million hectares (Mha), grassland by 0.7 Mha, plantation forest by 1.5 Mha, managed forest by 0.01 Mha and primary forest decreases by 4.6 Mha and Natural land decreases by 0.1 Mha [Calculations based on GLOBIOM output shared by David Leclère].

Whereas for some land cover categories net land cover change is small, there can be large changes in their gross land cover change. For example, for natural land, over the same time period from 2010 to 2050 there is a loss of 4.6 Mha (of this 4.2 Mha are converted to grassland and 0.4 Mha to plantation forest) but at the same time an increase of 4.5 Mha (of this, 4.4 Mha stem from abandoned grassland and 0.1 Mha from abandoned cropland; see Figure 5.5) leading to a 'net' decrease of 0.1 Mha. Another example of large gross changes is in the land cover category grassland: 7.1 Mha are lost during the period 2010 to 2050 (2.2 Mha to cropland, 0.5 Mha to plantation forest and 4.4 Mha to natural land) while there is also an increase of grassland by 7.9 Mha (3.7 Mha from primary forest and 4.2 Mha from natural land) [Calculations based on GLOBIOM output shared by David Leclère].

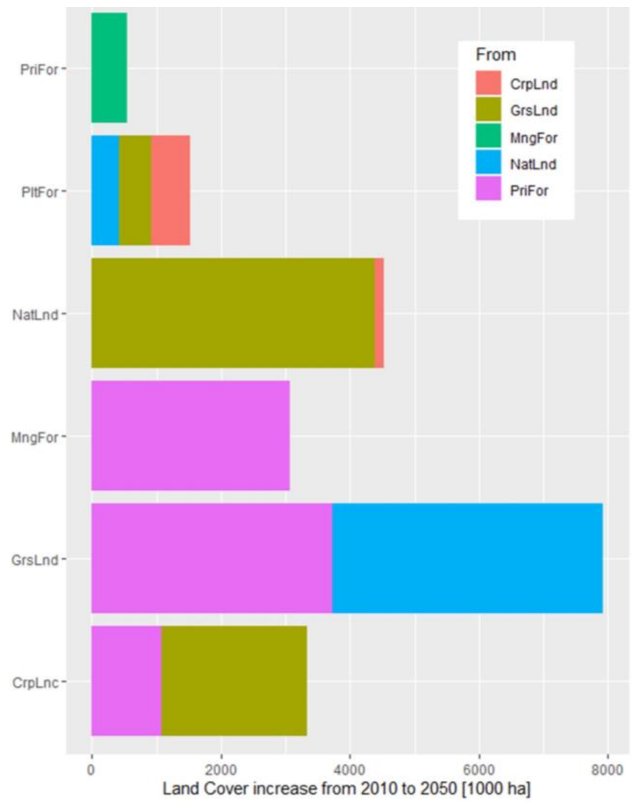

Figure 5.5. Overview of absolute land use change transitions projected by GLOBIOM for Argentina between 2010 and 2050 from land cover class to another. For example, the last row indicates the gains in cropland (over primary forest and grassland), which differs from net change in cropland cover as some cropland is abandoned (leading to an increase in natural land) and some other converted to forest plantations. Listed land cover classes refer to Primary Forest (PriFor), Plantation Forest (PltFor), Natural Land (NatLnd), Managed Forest (MngFor), GrsLnd (Grassland) and Cropland (CrpLnd)

5.3 Results

5.3.1 Prior model results to explain land cover change

Across all prior model setups, a correlation (positive or negative) was obtained for each variable for at least one land cover change transition with cropping input systems except for some variables from the default set-up (i.e. ‘irrigated area’, ‘high fertilisation area’, ‘low fertilisation area’ and ‘subsistence farming area’) and some variables from the Trase variable set-up (i.e. ‘soy harvested area in 2010’ as well as some export-market specific ‘market shares’, ‘distances to port’ and ‘distance to trade hub’). In contrast, the model showed correlations (Table 5.3) for biophysical variables (e.g. temperature, precipitation, slope, altitude, soil type), economic variables (e.g. ‘wood harvest cost’, ‘mean time to market’, ‘grass yield’, ‘soybean yield’), percent coverage with existing land cover at the beginning of the period (e.g. forest, natural land, grassland) and country-specific supply chain variables (e.g. 'distance to trade hub', 'distance to port', 'market shares').

Across all prior model setups, the correlation of variables depended on the type of land conversion and the variable setup considered. For all prior model setups, in case of the land conversion from grassland to cropland only six correlating variables were selected from the available input variables. In contrast, across all model setups conversion from primary forest to cropland had 16 correlating variables; from primary forest to grassland had 22 correlating variables; grassland to natural land had 21 correlating variables; cropland to grassland had 12 correlating variables and cropland to natural land had eight correlating variables.

Driver variables varied across land cover transitions as follows:

1) In the case of the <u>conversion of primary forest to cropland:</u>

- In the default (D in Table 5.3) variable set-up the model picks up as correlating the 'cropland coverage', 'forest coverage' as well as 'natural land coverage' at the beginning of the period, 'wood harvest tonnage', 'total population', 'rural population' and 'slope'.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 5.3) leads to the model additionally picking-up as correlating 'soy yield', 'soy harvested area in 2001' and 'soy harvested area in 2020'; 'Market share of EU Central East' and 'Distance to Tradehub of EU Central East'. However, running the prior model with both default and Trase variables also led to default-variables being dropped, namely 'forest coverage', 'wood harvest' and 'rural population'.
- Adding to the default variable set-up additionally local data variables (SPIPA S in Table 5.3), leads to the model picking-up as correlating from the SPIPA-variables 'distance to rivers', 'evapotranspiration' and 'annual precipitation'. However, now the model dropped all default variables except 'cropland coverage'.
- Adding to the default variables both TRASE and SPIPA variables combined (C in Table 5.3) leads the model to now only pick-up from the default variables 'cropland coverage', 'wood harvest cost' and 'total population'; from the TRASE-variables only 'soybean harvested area in 2001', but from the SPIPA variables still 'distance to rivers', 'evapotranspiration' and 'annual precipitation'. However, the model dropped, compared to the default variable set-up, 'slope'; compared to default plus TRASE, 'soy yield', 'soybean harvested area in 2020' as well as both 'Market share EU Central' and 'Trade Hub Distance EU' central get

dropped. Compared to default plus SPIPA, the model does not drop any of the 'SPIPA' variables.

2) For the conversion of primary forest to grassland:

- In the default variable set-up (D) the model picks up as correlating the 'cropland coverage', 'forest coverage' and 'natural land coverage' at the beginning of the period, 'wood harvest tonnage', 'wood harvest cost', 'grass yield', 'total population', 'altitude', 'slope' and 'soil type'.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 5.3) leads to no variables from the 'TRASE' dataset being picked-up as correlating. The only two variables which get dropped from the default set-up are 'forest coverage' and 'total population'.
- Adding to the default variable set-up additionally local data variables (SPIPA; S), leads to the model picking-up as correlating from the SPIPA-variables, 'distance to cities', 'distance to rivers', 'altitude', 'native forest coverage' and 'managed by law', 'annual precipitation' and 'effective depth'. However, now the model dropped from the default variables both 'forest coverage', 'natural land coverage', 'wood harvest cost', 'grass yield', 'altitude' and 'soil type'.
- Adding to the default variables both TRASE and SPIPA variables combined I leads the model to pick-up from the default variables, 'cropland coverage' and 'natural land coverage' at the beginning of the period, 'mean temperature', 'soil type' and 'irrigation area' (dropped compared to the default only were 'forest coverage', 'wood harvest tonnage', 'wood harvest cost', 'grass yield', 'total population', 'altitude', and 'slope'). In this combined variable-set, from the TRASE-variables as correlating is picked up only the 'Market share of China' (which is not picked up as correlating in any of the other variable combinations). From the SPIPA-variables, picked up as correlating (which were already correlating in the default plus SPIPA (S) set-up) were 'distance to cities', 'altitude', 'native forest coverage' and 'managed by law', 'annual precipitation' and 'effective depth'. New variables being picked up which were not already being picked-up with the default plus SPIPA set-up were 'national park coverage' and 'distance to roads'. Dropped was only the variable 'distance to rivers' compared to default plus SPIPA.

3) In the case of the conversion of grassland to cropland:

- In the default variable set-up the model picks up as correlating only the variables ‘natural land coverage’ and ‘total population’.
- Adding to the default variables additionally the ‘TRASE’-variables (T in Table 5.3) leads to only the variable ‘Market share China’ being picked up as correlating from the Trase variables whereas from the default variables, only the variable ‘total population’ gets dropped.
- Adding to the default variable set-up additionally local data variables (SPIPA), leads the model to pick up not a single variable as correlating from the SPIPA variables, but lead to drop from the default variables the ‘natural land coverage’.
- Adding to the default variables both TRASE and SPIPA variables combined leads the model to pick-up from the default variables only ‘rural population’ (was not correlating in any of the other variable combinations for this land transition) as well as the ‘natural land coverage’ which already got picked up as correlating from the default and the default plus TRASE (T) but not the default plus SPIPA (S) variable set. From the TRASE variables, only the ‘Market share of USA’ got picked-up as correlating which was not correlating in any of the other variable combinations for this land use transition. From the SPIPA variables only the variable ‘distance to rivers’ got picked up as correlating which was not correlating in any of the other variable combinations for this land use transition.

4) For conversion of cropland to grassland:

- In the default variable set-up the model picked up as correlating the ‘cropland coverage’, ‘grassland coverage’ and ‘natural land coverage’, ‘mean time to market’, ‘total population’, ‘altitude’ and ‘slope’.
- Adding to the default variables additionally the ‘TRASE’-variables (T in Table 3) leads from the TRASE variables to only ‘soy yield’ being picked-up as correlating. However, from the default variable data-set only one variable got dropped: ‘cropland coverage’; whereas the model picked up as new variable compared to only the default variable dataset (D) ‘grass yield’.
- Adding to the default variables additionally the SPIPA variables (S), leads the model to pick-up as correlating only two variables from the SPIPA dataset, namely ‘distance to cities’ and ‘annual precipitation’. Dropped compared to the default variable combination were ‘cropland coverage’ and ‘natural land coverage’, ‘altitude’, ‘slope’; whereas still correlating were ‘grassland coverage’, ‘mean time to market’ and ‘total population’.

- Adding to the default variables additionally both TRASE and SPIPA variables combined leads the model to drop from the default variables compared to running the model only with default variables (D) ‘cropland coverage’ and ‘grassland coverage’, ‘altitude’ and ‘slope’. Though still correlating compared to the default variable version (D) are ‘natural land coverage’, ‘mean time to market’ and ‘total population’. The model picks up as newly correlating compared to the default only (D) version ‘forest coverage’. From the TRASE variables the only variable which gets picked up as correlating is ‘soybean yield’ which is already correlating in the default plus Trase (T) variable combination. From the SPIPA-variables the same variables appeared correlating compared to running the model only with the default plus SPIPA variables: ‘distance to cities’ and ‘annual precipitation’.

Table 5.3. Variables showing positive (+) and negative (-) correlation to ESA CCI (2017) land cover changes from 2000 to 2010; estimated with quantile analyses. Tested variable sets were in each column Default-DownScale variables (D); Default together with TRASE-derived variables (T); Default together with SPIPA-derived variables (S) and Default combined with both TRASE and SPIPA-derived variables I. Rows with variables from the default set-up (red), TRASE (yellow) and SPIPA (green). Non-relevant columns are coloured in grey.

Variable	**PriFor to CrpLnd**				**PriFor to GrsLnd**				**GrsLnd to CrpLnd**				**GrsLnd to NatLnd**				**CrpLnd to GrsLnd**				**CrpLnd to NatLnd**			
Variable-sets	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C
Cropland coverage (in 2000)	+	+	+	+	+	+	+	+									-				-		-	
Grassland coverage (in 2000)							+										+	+	+		-			
Forest coverage (in 2000)	+				-									+	+	+				-				
Natural Land coverage (in 2000)	-	-			-	-		-	-	-		-					-	-		-				
Mean Temperature								+								+								
Mean Precipitation													-	-	-	-								
Wood harvest [tons]	+				-	-	-						-	-	-	-								
Wood harvest cost [$]		+		+	+	+							+	+	+	+					+			
Grass yield [tons]					-	-							-		-			-			+	+		+
Travel Time to Market																	-	-	-	-				
Total Population	-	-		-	-		-		-		-						-	-	-	-	-			
Rural Population	+											+												
Altitude					-	-								+			-	-						
Slope	-	-			-	-	+										+	-						
Soil type[22]					+	+2		+4					-	all	+4	-4					-	+3		-3
Irrigated area [ha]						-	-	-																

[22] Four different soil types were included: 'medium' (1), 'heavy' (2), 'stony' (3) and 'peats' (4).

Variable	**PriFor to CrpLnd**				**PriFor to GrsLnd**				**GrsLnd to CrpLnd**				**GrsLnd to NatLnd**				**CrpLnd to GrsLnd**				**CrpLnd to NatLnd**			
Variable-sets	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C
Yield [Tonne per Ha]		+																-		-				
Soy Harvested Area (in 2001)		-		-																				
Soy Harvested Area (in 2020)		+																						
Mshare China								-		-														
Mshare USA												-		-										
Mshare EU Central East		-																						
Mshare WestAfrSSA																-						-		
Distance to Port EU North														+		+								
Distance to TH EU CentralEast		-												-		-								
Distance to TH Middle EastNAfr														+										
National park coverage								-							-	-								
Moisture Balance															+									-
Distance to cities							+	+							+				+	+				
Distance to rivers			+	+			+					-				-								
distance to roads in 2014								+							-	-								
Altitude							-	-																
Evapotranspiration			+	+																				
Native forest and managed law coverage							-	-							-	+								
Annual precipitation			-	-			-	-											-	-				
Effective depth							-	-							-	-								
Provinces															-	-								-

5.3.2 Impact on land use change projections to 2050

We estimate the effect of including further driver variable-sets on the spatial distribution of projected land cover change by comparing the outcome of the DownScale model if including Trase-variables and SPIPA-variables compared to the default-version (Figure 5.6). As explained in the methodological section, the prior model setups do not affect the absolute amount of land cover change (determined by GLOBIOM), but only its spatial allocation.

Only considering the three land cover classes for which most land cover change is projected, namely cropland, grassland and primary forest, I find that adding either TRASE-variables or SPIPA variables increases the amount of cropland expansion in middle-northern Argentina compared to the output using only default-variables (Figure 5.6). However, besides this observation there are only few other differences visually observable from the national raster maps.

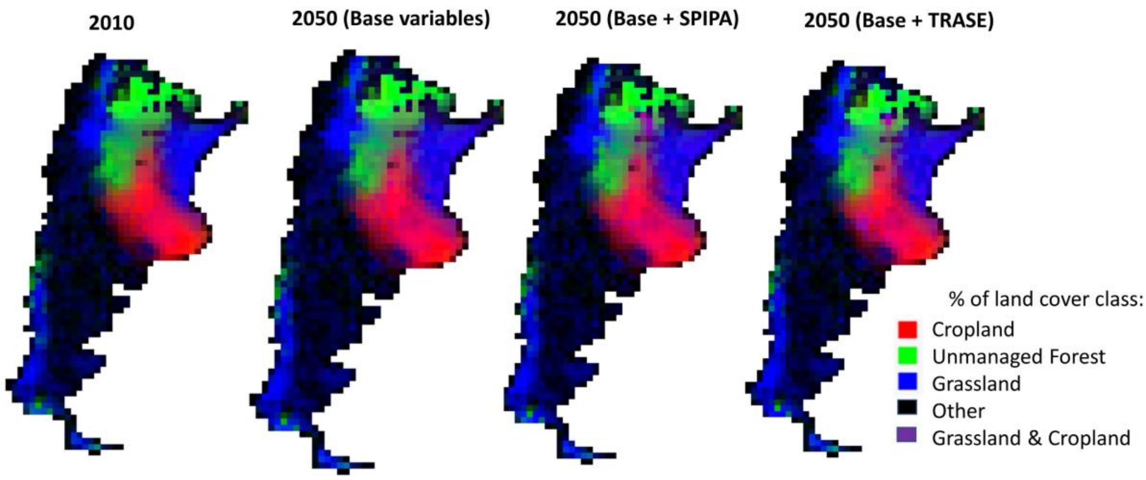

Figure 5.6. Raster map of Argentina depending on the percentage of the dominant land cover class in each grid cell (showing the continuous colour code): the redder it is, the higher the percentage of cropland in this grid cell; the greener it is the higher the percentage of unmanaged forest in this grid cell; the bluer it is, the higher the percentage of grassland in this grid cell. Therefore, violet is a mix of the colour blue (grassland) and red (cropland). Black means here that it is not dominated by any of the three key land covers here (i.e. cropland, unmanaged forest or grassland).

Figure 5.7 shows the pattern of projected net land conversion at pixel level for four different land cover types: cropland, grassland, primary forest and natural land. Compared to the default-version, including TRASE- and SPIPA variables leads to more 'hotspots' of land cover change rather than distributing it more equally across Argentinian existing agricultural land. For example, cropland increases in both the TRASE and SPIPA variable set-up by up to 53 % per simulation grid cell compared to the default variable set-up increasing up to 25 % (Figure 5.7). Similarly, for grassland including TRASE- and SPIPA variables leads to more increases in grassland in western Humid Pampas and Chaco biomes (see Figure 5.3). In the case of primary forest, including TRASE and SPIPA variables leads to primary forest loss of up to 40 % in some simulation grid cells.

The areas of highest cropland expansion are in the province Chaco and to a smaller extent in the province Santiago del Estero; mainly in the departments General Belgrano, Chacabuco, Doce de Octubre and Fray Justo Santa Mario de Oro.

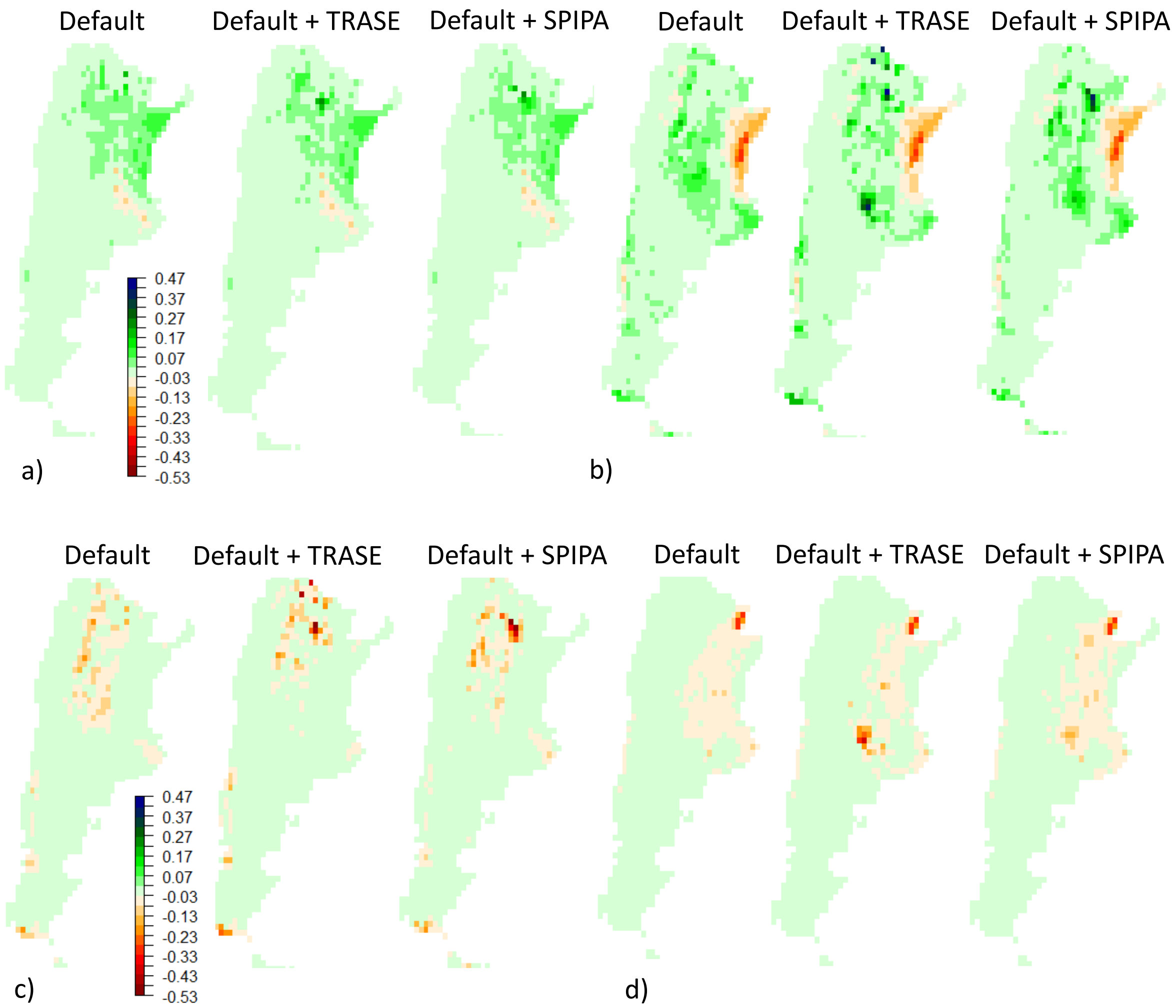

Figure 5.7. Percentage of change of total land from 2010 to 2050 for the land cover types of cropland (a), grassland (b), primary forest (c) and natural land (d) in each Simulation Unit. Comparison of output using either the default downscale version only or together with either SPIPA or TRASE variables.

Land cover change projections within Argentina are not equally distributed among the biomes. Using the default variable combination, cropland is projected to expand by 2.5 Mha between 2010 and 2050 according to the RCPRef SPA0 SSP3 scenario with the largest increase within the Chaco biome: 1.5 Mha of new cropland will likely appear within the Chaco compared to only 0.6 Mha in the Espinal and even a likely decrease of 0.04 Mha in the Humid Pampas (Figure 5.8). Similarly, with the default variable combinations of projected 4.6 Mha of primary forest loss across Argentina, the majority will be in the Chaco with 2.2 Mha for the default variable combination compared to a loss of only 0.7 Mha in the Humid Pampas and 0.4 Mha in the Espinal. In contrast, the majority of the loss of natural land will be in the Humid Pampas with 0.6 Mha and in the Espinal with 0.02 Mha (using the default variable combination).

Differences between the three variable combinations (default, default and TRASE, default and SPIPA) are largest for primary forest, grassland and abandoned grassland (Figure 5.8). Including TRASE-variables compared to the default setup leads within the Chaco to a conversion of 0.5 Mha more primary forest but an increase of grassland by almost 0.5 Mha from 2010 to 2050 compared to the default variable-set. In contrast, including TRASE variables compared to only the default variables leads to less conversion of primary forest in the Humid Pampas (0.4 Mha) and the Espinal (0.3 Mha). Including SPIPA variables compared to the default variable-set leads to more grassland expansion in the Humid Pampas (0.2 Mha), but less grassland conversion in the Espinal (0.2 Mha).

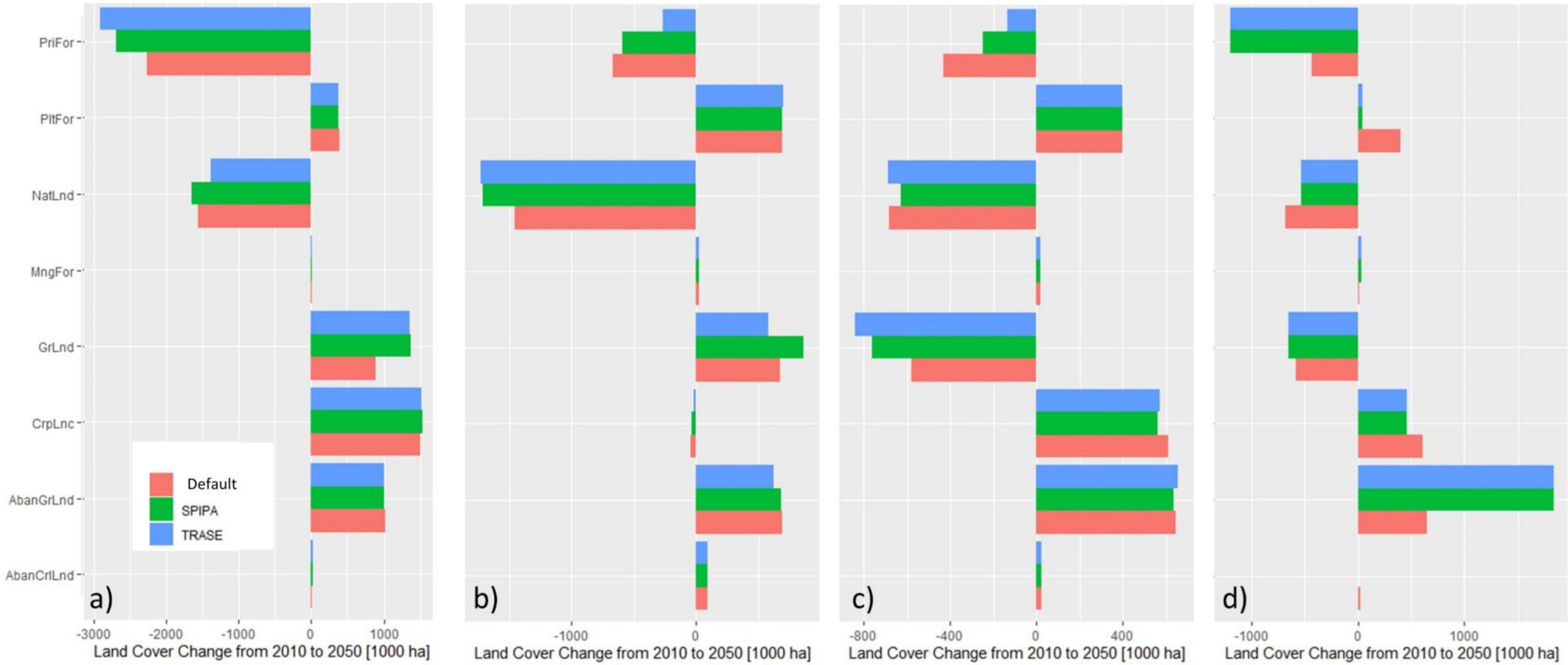

Figure 5.8. Net land use change of different land cover classes between 2010 and 2050 across different biomes in Argentina. Please note the different values on x-axes. for the biomes Chaco a), Humid Pampas b), Espinal c) and other biomes d) and different Variable set-ups. Listed land cover classes refer to Primary Forest (PriFor), Plantation Forest (PltFor), Natural Land (NatLnd), Managed Forest (MngFor), GrsLnd (Grassland), Cropland (CrpLnd), Abandoned Grassland (AbanGrLnd) and Abandoned Cropland (AbanCrlLnd).

5.4 Discussion

This study aimed to identify additional relevant variables explaining historical land cover change at sub-national level within Argentina using the DownScale model with the ultimate aim to improve the accuracy of spatial explicit land cover change projections. For this purpose I have incorporated into the prior model of DownScale spatially explicit supply chain data from the Trase platform as well as spatially explicit biophysical data from 'SPIPA'. This chapter showed that at least some of these additional variables are correlating with historical land cover change. I found that including either SPIPA or Trase variables lead to primary forest loss being much more restricted to few departments (namely General Belgrano, Chacabuco, Doce de Octubre and Fray Justo Santa Mario de Oro) within the Chaco rather than more equally distributed using default-variables (Figure 5.6). Being able to predict the few sub-national geographies likely experiencing most pressure on forests from agricultural expansion in future, would allow the targeting of interventions, and is likely making them more effective overall as a result.

As highlighted, this analysis is a first exploratory study to incorporate sub-national supply chain mapping into models that downscale global scenario models such as GLOBIOM. Initial differences in the spatial distribution of projected land cover change by 2050 between the three different variable combinations are not particularly stark, but this could potentially be explained by the fact that I did not include other variables which might have strongly influenced land cover change in the analysed time period between 2000 and 2010. For example, agricultural production in Argentina is known to be affected by export taxes on soybeans as 90 % of Argentinian soybeans are produced for export (Nolte et al., 2017). Alternative explanations could be drought events affecting farmers' income and therefore their financial capacity to expand production (Thomasz, Vilker and Rondinone, 2018).

Another challenge in explaining historical land cover change in Argentina could be the differences in available land cover maps and their land cover classifications. For this study I chose the global-scale ESA CCI land cover maps. It is possible that a national land cover map might be better in distinguishing native natural vegetation such as savannah-type land covers or pasture from grassland (see discussion in section 4.4.1.2). In a recent global study of historical cropland expansion between 1992 and 2015 by Eigenbrod et al. (2020), these authors also used the ESA CCI land cover map though to avoid error, they excluded the land cover classes 30 and 40 (mosaic of cropland).In contrast, in this study, the ESA CCI land cover classes 30 and 40 were included in 'cropland' (see

Krisztin and Wögerer, 2021). Eigenbrod et al. (2020) considered land cover classes 30 and 40 to be smallholder agriculture. As deforestation in Argentina is not driven by smallholder agriculture, including classes 30 and 40 as 'cropland' might overestimate deforestation. Perey-Hoyos et al. (2017) found that the ESA CCI land cover maps overestimate cropland globally. To which extent this is the case in Argentina Is unknown.

Several simplifying assumptions had to be made which may limit the validity of the findings. Firstly, I assumed that supply chain patterns are static over time. Reis et al. (2020) found that in Brazil over time scales of around ten years, supply chain patterns of companies were stable and consistent over time. It is likely that some supply chain variables such as distances to ports are more static over time than distance to logistic hub (e.g. silos or crushing facility) as over time it is likely that additional silos get built or traders using those silos change. Furthermore, as I estimated many supply chain variables specific to consumer markets, it is likely that some consumer market's supply chain configuration is more static (e.g. Europe) than others whose population and meat consumption is increasing (e.g., China or other Asian countries). It is also possible that political factors (such as the recent China-USA trade war) could re-shape sourcing decisions and therefore proportionally increase demand from some biomes within Argentina much more than from others.

5.4.1 Areas for Future Research

As this was only an explorative study with limited time available to analyse the benefits of including spatially-explicit supply chain data from Trase, there are many areas future research could focus on. One limitation of the study was that supply chains were assumed to be static. This limitation could be overcome by for example including information about the establishment of crushing facilities which would be available yearly from CIARA (2017). Possibly with this dataset a relationship could be established between the year of crushing facility establishment, soy processing volume of the crushing facility and localized land use change. Another limitation of this study is that I used driver variables from the time period of 2016-2018 to explain land cover change observed between 2000 and 2010. Therefore, for consuming markets which changed their supply chain between that period, it would be unlikely that these variables would be correlating.

Additionally, this study focused on adding variables explaining cropland expansion. However, Trase also has data available to improve projections of pasture expansion such as livestock density or egg production per department (Trase, 2020). Furthermore, as the land cover maps and their classifications vary for Argentina, it would be interesting to study if the projected land cover changes would be different with a national land cover dataset that is likely to better differentiate local natural habitat and natural grassland from human-used pastures.

Future research could include the modelled variables in a different way. In this study I included up to 150 different variables concurrently to explain land use change. However, some variables (especially those of the SPIPA dataset) are similar to the variables included within the default dataset (e.g. yearly temperature). Therefore, some of the default dataset variables could be replaced with some from the Trase or SPIPA dataset to test whether this might improve explanatory power. This more detailed analyses would help to understand uncertainty of parameters and improve the reliability of downscaled land use change projections (Chen et al., 2019).

Finally, for simplicity I did not change the national-scale quantities of projected land use change which are derived from the GLOBIOM model, but only the spatial pattern of these projections. However, it would be interesting to test whether Trase could help to improve the dynamic aspects of the GLOBIOM model itself as well. Trase data include the yearly changes of export flows per export market which could be useful for such modelling advances.

5.5 Conclusions

This exploratory study has shown that many of the supply chain variables, as well as additional local variables, introduced via the inclusion of data from Trase and SPIPA were found to be correlating with observed land use change. Therefore, it is worthwhile including these types of variables in the prior model which is linked to GLOBIOM. However, which variables were correlating was very much dependent on the type of the land cover transition being modelled. In addition to the important implications of the inclusion of this data on model dynamics, this study has also indicated that including additional spatially-explicit variables from the Trase and SPIPA-datasets may concentrate projections of the conversion of 'forests to grassland' and 'forest to cropland' to fewer, smaller, regions. Whilst highly tentative given the preliminary nature of this study, such conclusions (if verified in reality) would make it easier for governments and private sector actors to focus their efforts onto fewer forest frontiers. More research and data development is needed to verify these initial findings.

Chapter 6General Discussion

Despite the urgent need to produce commodities more sustainably and the accelerated availability of data, tools and methods to better understand environmental concerns in supply chains, the implementation of this knowledge into decision-making is lagging behind. To bridge this gap, the overall aim of this thesis is to consider supply chain actors' requirements in the development of environmental impact assessments of agricultural commodities with complex supply chains. Hereby I aimed to understand opportunities to build on sub-national supply chain mapping data. In this concluding chapter, I first summarise Chapters 1-5 and illustrate how they contribute to the aim of the thesis as well as to the individual research questions. Second, I discuss the thesis contribution and the overarching discussion points that emerged. Third, I reflect on the research of the thesis, highlight limitations and describe what this means for future research. Finally, I end this Chapter by illustrating the implications of these findings for practice and policy.

6.1 Summary of Chapters and key findings

The first research stage of this thesis was to engage with stakeholders and identify what knowledge end-buyers of forest-risk commodities would need so that they can utilise sub-national supply chain mapping data and improve environmental sustainability in complex supply chains (Chapter 2). I identified that stakeholders have a need to consider multiple dimensions of sustainability in decision-making. As a response to this need, the second objective of the thesis was to apply the sub-national trade flows to several impacts associated with water and land use (change) for soybean production (Chapter 3). Secondly, stakeholders articulated a need for robust estimates of environmental impacts (Chapter 2). Therefore, I also aimed to understand the sensitivity of the results of Chapter 3 to different methodological and data choices as well as assumptions on farming practices (Chapter 4). Third, stakeholders mentioned a need to understanding how environmental impacts might evolve in future (Figure 6.1). As a response to that, the last aim was to explore the effect of incorporating sub-national supply chain mapping data into a predictive land use change model (Chapter 5).

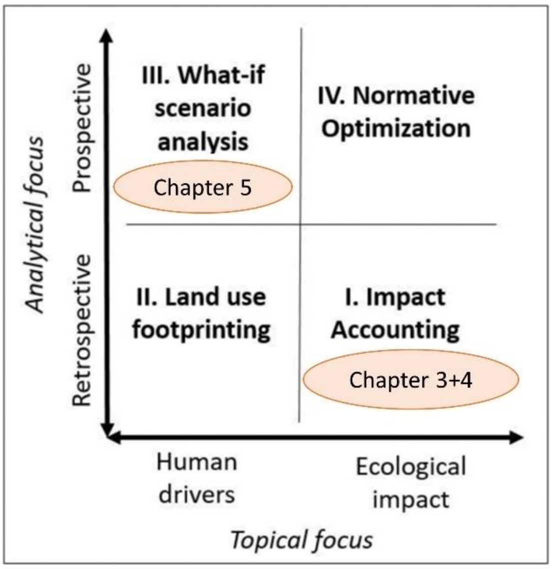

Figure 6.1. Categorization of quantitative Chapters depending on their research objectives (adapted from Bhan et al. (2021)

In Chapter 1, I describe the problem space in which this PhD thesis at the science-policy-interface fits. It is a challenge to meet the human population's increasing demand on food while tackling climate change, biodiversity loss and degradation of ecosystems and natural resources. The importance of this challenge is acknowledged by the private and public sector and illustrated through commitments to eliminate commodity-driven tropical deforestation. However, despite the increasing availability of data and information aiming to transform agricultural production of traded commodities, implementation of this knowledge into decision-making is slow. Therefore, there is an urgent need to engage with stakeholders to identify how research could be made more useful in practice. In this context, LCA is an important decision-support tool to identify key impact hotspots along the entire value chain of products and therefore improvements strategies (Crenna et al., 2020). However, LCA is often limited in the sub-national detail it contains to account for the heterogeneity in environmental impacts (Patouillard et al. 2019). Another gap is that existing research has often focused on a single producing country in isolation (Gardner et al. 2019). This is limiting the relevance to multi-national companies and governments with globalised supply chains (Bhan et al. 2021). Additionally, there is a lack of inter-comparison about the effect of different available data sources, methodological choices or assumptions on estimated water and land use (change) impacts due to agri-commodity production. Therefore, these identified research gaps directed the focus of the following chapters.

The objective of Chapter 2 was to understand how different stakeholders involved in shaping decision-making in the context of end-buyers of ‘forest-risk’ commodities themselves see limitations in knowledge and barriers to progress within globalised complex supply chains. For an in-depth exploration, I adopted a qualitative approach based on semi-structured interviews and focus group discussions of manufacturers and retailers sourcing agricultural commodities, NGOs, consultancies and certification bodies. I found that sub-national supply chain mapping data could be made more relevant to end-buyers by: 1.) linking to multiple environmental impacts for a more holistic consideration of sustainability, 2.) covering multiple producing countries consistently as multi-national companies have globalised supply chains and 3.) allowing to understand how future impacts might evolve as a response to possible decisions (Figure 6.1). However, opinions ranged heavily between interviewees about whether research findings should be communicated in a more simplified manner (e.g., expressed in a single metric) to avoid delaying action or by acknowledging the complexity inherent In such assessments to lead to better decisions in the long-term. Another finding was that the perceived conflict of interest between different actors along the supply chain is hindering progress on sustainability challenges.

Chapter 5 builds on the research gap identified in Chapter 2 by linking sub-national trade flow data to impacts of water and land use (change) for soy production to improve the spatial resolution of existing impact assessment and identify arising trade-offs. Using Life Cycle Assessment principles and spatial data analyses, I estimated impacts on land use change emissions, biodiversity, water scarcity and soil productivity related to soybean exports from Argentina, Brazil and Paraguay. While the regions with largest soy-induced LUC emissions were located in the north and northeast of Brazil (Para, Rondônia, Piaui) as well as northern Argentina (Salta), regions with highest biodiversity impacts were in the coastal rainforest of Paraguay (Alto Parana, Canindeyú, Caaguazú) and southern Brazil (Santa Catarina). In contrast, regions with largest soil productivity loss were found in the southeast of Brazil (Santa Catarina, Rio Grande do Sul, Parana). These differences between soy producing jurisdictions also influenced which consuming countries had the largest footprints depending on their sourcing pattern: Brazil had the largest soil productivity loss and biodiversity footprint, Spain the largest LUC carbon footprint and China the largest water scarcity footprint. Nevertheless, variability within states was high across all studied impact categories highlighting the benefit of sub-national supply chain mapping data for spatially-explicit land and water footprints. However, a high level of uncertainty remained as hotspots of LUC carbon footprints differed to those reported by other authors (e.g. Escobar et al., 2020) using alternative spatial data and taking different methodological choices.

To better understand sources of uncertainty discussed in Chapter 3, the objective of Chapter 4 was to analyse the sensitivity of the estimated results to different choices and assumptions taken in the application of LCA methods. To date, a lot of research aiming to reduce uncertainty of agricultural products in LCA has focused on improving the spatial resolution of field data (e.g. yield) or indicators (e.g. water scarcity, biodiversity loss). However relatively little research exists on how the uncertainty arising from the choice of method (e.g. length of amortisation period) or data (e.g. land cover, carbon density, double-cropping) translates into uncertainty in estimated environmental impacts. I find that choosing a 5-year time period to account for direct LUC carbon emissions instead of 20 years triples LUC emissions for some states outside of the Amazon. Additionally, the choice of forest carbon dataset can double LUC emissions for some states in Argentina and Paraguay. Biodiversity damage is most influenced by the inclusion of the grassland land cover in the transformed area in the biome Pampa. Water scarcity is more influenced by the spatial variability between states than the application of monthly (instead of annual) water scarcity estimates. In contrast, soil productivity loss is more influenced by assumptions on farming practices (tillage) than the spatial variability of the indicator between states. However, the importance of these factors depends on the geographic location of the producing region. This study illustrates that besides more spatially-resolved data, there also needs to be harmonisation and guidance in methodological and data choices to reduce uncertainty in environmental impact estimates. Agreeing on standard data and methods to quantify LUC emissions will be crucial to successfully implement policies of multinational companies and consuming countries aiming to reduce impacts of global agricultural trade.

As a response to the identified stakeholder needs to understand future impacts of potential decisions and policies (Chapter 2), the objective of Chapter 5 was to explore whether models projecting land use patterns driven by international agricultural commodity demand can be improved by incorporating sub-national supply chain mapping data. To date global economic land use models can be limited in their spatial resolution by often only linking at the national level producing to consuming countries, limiting the ability to account for the heterogeneity in environmental impacts of agricultural production. Using a partial equilibrium economic model with a global framework but high specificity in 165ork165ultureal sectors, I tested for the effect of including sub-national supply chain mapping on the difference in the spatial allocation of land use change patterns in Argentina until 2050. I found that including Trase highlighted a spatial concentration of the cropland expansion at the detriment of forest in few grid cells in the northeast of the tropical dry forest Chaco. In these grid cells, the increase in cropland was around 53 % higher compared to excluding Trase data in the land use change calibration. Being able to better predict where future land use change would be concentrated could help to focus efforts and policies on those jurisdictions. This study is an exploratory attempt to integrate sub-national supply chain mapping data from Trase into the global Partial Equilibrium model GLOBIOM (Global Biosphere Management Model). Therefore, many suggestions for future research remain and were discussed which – depending on further methods development – would potentially help to inform decision-making towards reducing the impact of trade in agricultural commodities in future.

6.2 Thesis contributions and points of integrated discussion

Within each of the analytical Chapters (Chapters 2-5) the specific contributions and relevance of the work conducted have previously been discussed within dedicated Discussion sections per-Chapter. Nevertheless, there are emergent cross-cutting themes which are now discussed below.

6.2.1 Data: balancing local and global coverage

A core aspect that arose in all analyses was the challenge of balancing detailed information that is better adapted to a local context with a desire for coverage of larger geographies, thus enabling comparison across different regions. For example, Chapter 4 illustrated the large difference in identified hotspots of soy-induced LUC emissions for some biomes using global land cover maps compared to national Brazilian alternatives as in Escobar et al. (2020). The differences between global and local maps of land cover (e.g. Winkler et al., 2021), carbon density (e.g. Pötzschner et al., 2022) or species richness (e.g. Primack et al., 2018) are partly due to technical limitations of Earth Observation to increase the spatial resolution or delineate land cover types (Liu et al., 2021) but also due to different definitions adopted in the development of these maps. For example, the widely used global datasets by Hansen et al. (2013) define deforestation as a loss in forest cover, whereas the Brazilian government defines 'deforestation' as a change in land use from forest to cropland in their dataset PRODES (Portuguese: Brazilian Amazon Deforestation Monitoring Program; Numata et al., 2011). Therefore, the Hansen et al. (2013) definition would overestimate deforestation as it would include forest loss in plantations and managed forests which is not a change in land use (Tropek et al., 2014). However, alignment with national policies such as the Brazilian Forest Code (which is supported with PRODES; e.g. Soterroni et al. 2018) or the Argentinian Forest Law (Nolte et al., 2017) is an important consideration for data selection. Nevertheless, a limitation of national land cover products can be that they are often not available annually, restricting their ability to monitor changes over time (Souza et al., 2020). Overall, researchers need to carefully select which data are best suited for the purpose of their study.

As an example, to support the implementation of global initiatives such as the Sustainable Development Goals (SDGs), Convention on Biological Diversity (CBD) and the COP26 Glasgow Convention, reliable data are needed which are globally consistent (Potapov et al., 2022). Actors such as multi-national companies and consuming countries have globalised supply chains and therefore require standardised and robust data, methods and indicators to monitor compliance to international trade agreements and supply chain policies. To date there are also no standardised systematic sustainability assessments to quantify how EU trade policies contribute to global policy targets such as CBD or SDGs and their associated targets (Kuik et al., 2018). However, while satellite-derived information such as deforestation is readily available, there is a lack of data about farming practices such as double-cropping, tillage and irrigation which would be crucial to assess sustainability of agricultural trade more holistically. In this context, balancing the need for simple approaches with comprehensive assessments capturing the complex nature of eco-agri-food systems (impacts depend on fine-scale land use intensity, landscape fragmentation and local ecosystems) will remain a practical and methodological challenge.

6.2.2 Complexity

Providing scientific evidence on how to tackle environmental problems driven by global trade in agricultural commodities is a challenge. In a complex system where consumers are linked to producers through globalised supply chains, it is difficult to describe cause and effect relationships (Newig et al., 2020). In these systems, effects can be indirect, cascading, non-linear or have feedbacks (Liu et al., 2021). Therefore, scientific knowledge about these systems is often uncertain or incomplete (Grove and Pickett, 2019). For example, there are knowledge gaps with measuring the variety of environmental impacts associated with the trade in agricultural products (Liu et al., 2021). In this context, recent improvements in transparency and traceability of global supply chains have helped to reduce this knowledge gap and ascribe responsibility to different actors (Gardner et al., 2019). Escobar et al. (2020) build on these novel data to create fine-scale greenhouse gas footprints of imported soybeans. However, these authors stress that their research should be considered a first step. To better guide decision-making for sustainability in supply chains, research should account for multiple environmental impacts to identify potential synergies and trade-offs. I have contributed to this existing research by building on Escobar et al. (2020) and responding to the stakeholders' knowledge gap identified in Chapter 2 to estimate spatially-explicit impacts of soybean production across four dimensions of environmental sustainability (Chapter 3). Nevertheless, during the qualitative stage of this research, stakeholders highlighted knowledge gaps (Chapter 2) which I could not fully address in my research. For example, some stakeholders mentioned that they would like to understand unintended consequences in the system when making decisions such as by better understanding social impacts, land conversion leakage effects to other biomes, or how impacts might evolve in future. At this time, analytical models aiming to account for the complexity of environmental problems in global trade systems either are not yet available or are not suitable to account for the complexities of these challenges. Examples of these complex interactions are land use changes and its multiple causes that work over multiple scales which are difficult to represent in models (Grove and Pickett, 2019). Therefore, these stakeholder knowledge gaps remain an ongoing research challenge.

One approach to emphasise the complexity inherent in impact assessments could be to incorporate the variability and uncertainty in estimates of environmental impacts in the communication of findings. To illustrate this, I have tested the sensitivity to different available alternative data and assumptions in Chapter 4. Nevertheless, while methods applied in Chapter 3 and 4 have been developed to inform stakeholders about environmental impacts of ongoing (historical) trends in land use change (bottom right quadrant in Figure 6.1), these methods are not fit for the purpose to guide decisions on 'what if' scenarios where end-buyers change their sourcing to an alternative region (scenario analysis, top left quadrant in Figure 6.1). Therefore, in Chapter 5, I attempted a first step towards incorporating traceable supply chain data into forward-looking land use change models to better link actors to future impacts. However, there is a risk that the complexity (multi-dimensionality) of the problem space overwhelms actors leading to paralysis (Termeer and Dewulf, 2019). Broadening the information that is provided increases the complexity by incorporating multiple indicators, geographies, biomes and sensitivity to normative choices. However providing this complexity reduces the risk of shifting the burden to other impact categories, geographies, biomes or commodities (Gardner et al., 2019). A challenge in this context is to harmonise data to facilitate comparability of information while adjusting to the local context or users (Boström et al., 2015). Therefore, researchers, policy- and decision-makers need to carefully balance how much complexity is needed which will depend on the research question and the scale of the expected commodity demand. However, over-simplifying complex coupled environmental problems can distract from identifying potential solution pathways (Friis et al., 2016). Therefore, given the inherent complexity and uncertainty of the global agricultural supply chain system and the challenge of interpreting and taking action based on this information, Boström et al. (2015) argued that pathways will need to be walked through so that through continuous learning knowledge is developed. This thesis has demonstrated the usefulness of an interdisciplinary approach to develop knowledge to understand complex sustainability challenges. An approach useful here as Thornton (2017) suggests is to select the method and the respective discipline (e.g., natural sciences or social sciences) that best fits the research question rather than being restricted by the tools (methods) available within the boundaries of a single discipline.

6.3 Reflections, limitations and implications for future research

The findings of this research have been highlighted in section 6.2 and in the individual analytical Chapters of the thesis, illustrating the contribution of this thesis to existing research in the field. Limitations of this thesis have also already been discussed in individual Chapters however, in this section, limitations will be discussed further in more detail, including as the basis of providing recommendations for ongoing research activities.

6.3.1 Qualitative engagement with stakeholders to identify needs

Balancing sampling size and the number of included actor groups along supply chains is a challenge. During the qualitative data collection phase, the scope of the research limited sampling to actor groups most distant to producing regions. These stakeholders were selected because of their distance from producing regions and separation via multiple intermediaries (e.g. traders) common in complex supply chains (Zu Ermgassen et al., 2022). This location in the supply chain means that it is hard for them to identify the origin of their sourced commodities and associated impacts. These stakeholders are arguably most in 'need' of supply chain mapping data, particularly given the growing expectations placed on these stakeholders (see Chapter 1). As discussed in section 2.4.3, however, this focus excluded farmers as they were not considered core users of sub-national supply chain mapping data. Whilst this methodological choice was intentional, it does mean that the results of Chapter 2 cannot shed light on the local socio-economic drivers of environmental impacts in producing regions or evaluate the likely success of solutions (a knowledge gap that was suggested by some interviewed NGOs; e.g. to incentivise production on degraded land). Including farmers in the interviews might have also identified different priority sustainability concerns. For example, Newig et al. (2020) argued that in relation to soybean trade, local Brazilians are more likely concerned about pesticides, water pollution or land rights, whereas concerns of German NGOs are more likely to be around protecting tropical forests. Because, in this thesis, the qualitative research informed the quantitative research, including actor groups closer to producing regions (e.g. farmers) in the qualitative research could have changed the focus towards understanding the environmental impacts of farming practices (e.g. fertiliser application, land preparation, pesticide management).

Additionally, since the beginning of my qualitative data collection in early 2020, the policy landscape has changed with the introduction of the EU's regulation for deforestation-free products (EC, 2021b), UK Due Diligence on forest-risk commodities (Defra, 2022) and the declaration on forests and land use at the UN Climate Change Conference in Glasgow (UN COP, 2021). Therefore, in the last two years the potential importance or relevance of more granular impact assessment to commodity traders has changed, as they will likely shortly be held responsible to comply with the EU's proposal for a regulation on deforestation-free products (Zu Ermgassen et al., 2022). The approach I have chosen here (semi-structured interviews) allowed richness and depth in participants' responses but was also time-consuming thus limiting the sample size and thereby reducing generalisability. Yet this is typical for qualitative research (Bryman, 2001). However, future research would benefit from including more 'voices' of actor groups such as farmers, traders and sub-national or national governments. Being inclusive to include a wide range of stakeholders will allow consideration of broader sustainable development goals and avoid efforts being restricted to incremental changes (Bastos Lima and Persson, 2020).

Additionally, as I found divergent opinions, for example on the need to acknowledge complexity in contrast to a need for more simplification of information, future research could consider multi-stakeholder workshop approaches. In contrast to interviews, workshops could help to seek consensus among participants on the necessary level of complexity, or at least to better understand where needs align and where they do not.

6.3.2 Choice of indicators applied in this thesis

The indicators selected in this study (i.e. LUC emissions, biodiversity damage, water scarcity and soil productivity loss) had the advantage of being available at global scale. Therefore, if harvested area maps and sub-national supply chain mapping data were available, the approach presented here could be applied to any other region in the world. However, there are also shortcomings of the indicators selected in this thesis such as limited sensitivity to account for land use intensity, spatial variability and local context. I selected the indicators for LUC emissions for alignment with the Greenhouse Gas Protocol (WRI/WBCSD, 2011), for soil impacts the approach recently developed by Sonderegger et al. (2021), and for biodiversity and water scarcity the indicators recommended by the global UN Life Cycle Initiative (2018). For the selected indicators of LUC emissions and soil productivity, I could maximise the benefits of detailed sub-state supply chain data to improve the regionalisation in LCA. However the highest spatial resolution available of the indicators recommended by the Life Cycle Initiative was the level of ecoregions for biodiversity (Chaudhary and Brooks, 2018) and watersheds for water scarcity (Boulay et al. 2018). These guidelines ultimately limit the ability to fully account for the spatial heterogeneity in water scarcity and biodiversity. For example, previous studies showed that impacts can be quite variable of biodiversity within a large ecoregion like the Cerrado (e.g. Durán et al., 2020; Green et al., 2019) or of water scarcity within a watershed (Mekonnen and Hoekstra, 2016). Another limitation of the approach recommended by the Life Cycle Initiative, is that it does not seem to fully meet the needs of businesses according to a recent review about biodiversity assessments of value chains by Crenna et al (2020). The Life Cycle Initiative's indicator only considers impacts on the biodiversity dimension of species richness (Chaudhary and Brooks, 2018)., However, Crenna et al (2020) found in their review that, additionally within the business domain, the dimension of species abundance was quantified. Nevertheless, as previous research has shown that the choice of considered biodiversity dimension can affect the results (Marquardt et al., 2019; Chaplin-Kramer et al., 2017), future research would benefit from applying multiple biodiversity indicators to better account for the complex nature of biodiversity. To overcome the limited spatial and temporal resolution of the Boulay et al. (2018) water scarcity indicator, Mekonnen and Hoekstra (2016) suggested an indicator which accounts for monthly fluctuations in water scarcity and is available at a higher spatial resolution (55 x 55 km at the equator). However, this recommendation did not gain global consensus within the LCA community. Another limitation of the Boulay et al. (2018) indicator to inform consumer and supply chain decisions is that it does not account for the local regulation of water through infrastructure or legislation thereby affecting how much water is available for agriculture. Therefore, future research should apply multiple indicators to compare the results across different geographies to identify why and where results are different which is particularly relevant for highly debated concerns such as biodiversity and water scarcity.

6.3.3 Towards holistic sustainability estimates of agricultural trade

In this thesis, I only studied direct land use change and estimated environmental impacts for which indicators were available with a sub-national spatial resolution. The broad geographic scope of my analysis enables understanding of the implications of sourcing from across a range of different producing regions and identifies geographic impact hotspots and trade-offs. However, I could not completely respond to the stakeholder needs identified in Chapter 2 in terms of wanting to understand land use change leakage to other biomes. Leakage is a form of indirect land use change due to a land use intervention (e.g. conservation policy), which leads to land use change elsewhere reducing the overall benefit of the local intervention (Meyfroidt et al., 2018). A limitation of the commodity and spatially-explicit approaches to assess LUC emissions is that they can only account for direct causes but not for the underlying causes (e.g. change in demand for cropland due to policy changes or behaviour shifts). Therefore, the direct LUC approaches can underestimate LUC emissions allocated to a specific quantity of commodity (Bhan et al., 2021). Another limitation of the direct LUC approach is that the results are highly sensitive to the amortisation period chosen (Schmidt et al. 2015), as shown in Chapter 4. In a study of soybeans in Brazil, adopting an indirect approach increased LUC emissions by more than four times compared to a direct approach as the area cultivated with soybeans increased rapidly in Brazil (Persson et al. 2014). In future, with enhanced availability of yearly crop raster maps and an improved understanding of land use change dynamics (emerging for some South American regions; Baumann et al., 2022), accounting for indirect LUC emissions will likely become more robust and reliable. This will have the potential to respond to the needs identified in Chapter 2.

Furthermore, stakeholders articulated an interest to understand social impacts and unintended consequences in supply chains (Chapter 2). Therefore, the results of this thesis cannot completely respond to this need in terms of a full holistic understanding of agricultural commodities' sustainability impacts which are in reality more complex than modelled in Chapter 3 and 4. Most previous studies have focused only on a single impact category in isolation to assess impacts of agricultural trade such as greenhouse gas emissions (e.g. Hong et al., 2022), biodiversity (e.g. Marquardt et al., 2021; Chaudhary and Brooks, 2018; Lenzen et al., 2012) and water (e.g. Lathuillière et al., 2021). The few studies attempting to cover multiple metrics did so with a coarse spatial resolution at the producing country level (see e.g. Xu et al., 2020). I have responded to this gap by estimating four different environmental impact categories and identified trade-offs. For example I found that regions with small LUC emissions can have large soil productivity loss from water erosion (Chapter 3 and 4). In the broader community, a lot of indicators are available (such as more than one hundred for biodiversity alone used to measure progress towards the Aichi targets; Crenna et al., 2020). However, many of these indicators are not readily operationalizable for decision-making either because the necessary data are not available or they are not in a framework companies are familiar with such as LCA.

An analysis of social impacts was out of scope of this study but stakeholder interest to understand social impacts in supply chains is increasing (e.g. Chapter 2), guidelines are emerging for companies to set social goals (Accountability Framework, 2022) and methods are emerging to quantify social impacts (Pollok et al., 2021). However, as the review about social life cycle assessments by Pollak et al. (2021) has pointed out, a lot of more research is still needed to standardise approaches and better connect them to political targets. Future research should also aim to improve the quality of data underpinning global social footprints such as modern slavery, forced labour or child labour to improve the accuracy of national and sectoral estimates (Shilling, Wiedmann and Malik, 2021).

6.4 Implications of findings for practice

This research has shown that improvements in spatial granularity can make estimated agricultural impacts more relevant and robust for decision making by reducing uncertainty of estimates. However, incorporating this detail within commercial LCA software is challenging, limiting its operationalisation (Hellweg and Milà I Canals, 2014). The most commonly used LCA software (e.g. GaBi and SimaPro) or LCI databases (e.g. Ecoinvent) regionalise LCIA methods by providing region-specific inventory flow names (e.g. soybean production, BR-MT) for each regionalized impact category. Therefore, this regionalization approach limits the number of different inventory flows that can be incorporated (Patouillard et al., 2018). For example, in Ecoinvent, LUC emissions for soy are available at the state-level for Brazil but for smaller countries like Argentina or Paraguay only national-level differentiation is available (Donke et al., 2020). Therefore, users of these types of software or databases would need to process spatial inventory data or use spatially-explicit characterization factors (Li et al., 2021), which can be time consuming and requires GIS skills which is not common among LCA practitioners (Kulak et al., 2018). Alternative LCA software has been developed, which incorporates GIS functionalities such as uploading shapefiles with spatially-explicit characterization factors such as openLCA or Brightway (Patouillard et al., 2018). While Brightway is mostly used by researchers, openLCA requires some GIS skills (Patouillard et al., 2018) limiting its uptake by practitioners. Therefore, mainstreaming regionalization among the LCA community could be simplified by aggregating characterization factors to state or country level to reduce the number of inventory flows in common software. Lathuillière et al. (2020) suggested to aggregate characterization factors by weighting by trade volumes referred to as 'commodity supply mix' (CSM). This research showed that calculating averages of state's LUC emissions with a CSM (rather than adopting an equal weighting for all municipalities) changes which states are identified as geographic hotspots. Therefore, guidelines are needed about how characterization factors should be aggregated from finer to coarser scales.

The CSM could also help to harmonise the various spatial scales (e.g. ecoregions, watersheds, country boundaries) in LCA into a common administrative unit familiar to practitioners (e.g. country or state) as the diversity of spatial scales in which characterization factors or inventory data are available was mentioned as hindering progress of regionalisation approaches in practice (Mutel et al., 2019). To facilitate access by practitioners without GIS capability or software, Pfister, Oberschelp and Sonderegger (2020) created a specific spatial layer. This layer includes all spatial entities relevant in LCA (e.g. ecoregions, watersheds, country boundaries, major cities) in a format accessible with Google Earth. However, while Google Earth allows to visualize spatial data, manipulation of these data is challenging for practitioners with limited coding skills.

Reliable estimates of commodity production's impact of land and water use need to account for sub-national heterogeneity. This research has shown that while indicators and spatial data are available at global level, converting these data into useful information about spatially-explicit impacts requires specific skills. For example crucial skills are spatial data analyses with a Geographic Information System (e.g., ArcGIS or Google Earth Engine) and coding language such as R to process these large data sets. However, many LCA practitioners do not have these skills (Kulak et al., 2018) limiting the uptake of regionalization approaches within the LCA community. Therefore, as a response to the need for a more user-friendly solution for practitioners to estimate spatially-resolved agricultural impacts, a web-based platform 'GeoFootprint' has been developed by the consultancy Quantis (Frischknecht et al., 2019). GeoFootprint combines spatial maps (e.g. land cover, cropping areas, soil types) with developed environmental LCA indicators to process spatial data, estimate and visualize environmental impacts of agricultural production at global scale (Frischknecht et al., 2019). However, as GeoFootprint requires purchase of a license, access of this information is restricted to few actors within global supply chains. Limiting access about sustainability knowledge to a few supply chain actors can be a barrier to effective sustainability governance (Abson et al., 2017). Another limitation of the GeoFootprint platform is that some of the underlying data is outdated with for example crop-specific yield and harvested area maps from

2000 (based on Ramankutty et al., 2008). Although uploading of additional data is possible, finding reliable alternative timely data requires time. Therefore, this reduces the potential relevance of the information provided as timeliness of information was identified as a stakeholder need in Chapter 2. Consequently, efforts might be rather directed towards developing a public platform bringing multiple types of up-to-date and relevant information together. For instance, this could be building on some characteristics of cloud-based spatial data analyses platforms allowing to easily share large spatial data with users having limited computing capacity or GIS capability. Examples of these are Google Earth Engine (GGE, 2022) or Microsoft's planetary computer (Microsoft, 2022).. Therefore, cloud-based data collection, storage and computing allow the distribution of spatially-detailed information to a much wider group of potential users who have been previously limited in data storage capacity, computing power or spatial data analysis capability. In future, to help mainstream the use of spatially-detailed information on supply chains impacts to decision-making, an open-access platform might be needed which brings together various spatial data and converts it into indicators practitioners are familiar with.

6.5 Implications for policy

Policies aiming to tackle global environmental problems caused by trade in agricultural commodities need to consider multiple environmental impacts together rather than in isolation. While a lot of research still needs to be done to consider all relevant dimensions of sustainability, I have started this by showing that although soy-induced land use change emissions are largest in tropical forests, impacts on biodiversity and soil productivity loss, can be larger outside of these regions. Especially for land use, trade-offs are common and focusing on a single goal (e.g., climate change mitigation) will most likely negatively affect other benefits of land (e.g., food production, species conservation, water provision) (Meyfroidt et al., 2022). Therefore, efforts to mitigate climate change should explicitly account for other benefits of land such as biodiversity conservation, water provision or food security (Boysen et al., 2017). While the need to consider interactions between different goals was highlighted at a global level through the Sustainable Development Goals (SDG) in 2015 (Nilsson et al., 2018), there is limited evidence that this has changed the design of national and international policies (Biermann et al., 2022). This reflects what I found amongst private sector actors, where a lot of end-buyers focus on tackling a single issue such as climate change or tropical deforestation without simultaneously considering other environmental impacts of agricultural production. Gardner et al. (2019) explain this with the fact that people perceive as important what is visible to them. Therefore, the increased transparency in global commodity supply chains risks overfocusing on visible aspects such as few indicators or geographies (Gardner et al., 2019). This thesis has illustrated that data and indicators are available to extend the visibility for a) ecosystem conversion beyond tropical deforestation such as loss of other non-forest ecosystems, b) environmental impacts beyond LUC emissions such as biodiversity, water scarcity and soil productivity loss and c) biomes and countries beyond Brazil and the Amazon to, for example, Argentinian and the Pampa biomes (EU, 2022). While this thesis can be considered a step towards a more holistic assessment of the sustainability of trade in agricultural commodities, understanding all relevant trade-offs and co-benefits arising in this complex system and knowing how to best manage them across scales (e.g. highlighted in Kozicka et al., 2022) will remain a challenge.

For international trade policies to be more holistic by incorporating multiple dimensions of sustainability, more political dialogue is needed between different actors along the supply chain to agree on common goals of natural resource use and definitions outlined in environmental policies (e.g. tropical deforestation). This problem is illustrated by the large difference in soy-induced land use change emissions found in my research when using national, compared to global, land cover definitions and maps. To date various definitions of 'deforestation', cut-off dates for land conversion or included commodities exist between different policies. Stakeholders have identified this conflict in interest between different actors along the supply chain as a perceived barrier towards progress of sustainability in supply chains (see Chapter 2). European end-buyers of South-American soybeans felt unable to demand of producing governments more ambitious sustainability efforts than what is legal in their own countries. This is also illustrated for example in the negotiations of the trade agreement between Mercosur countries (Argentina, Brazil, Paraguay and Urugay) and the European Union. Brazil successfully pushed for a lowering of the sustainability standards (Newig et al., 2020) resulting in an agreement considered to 'fail the sustainability test' according to scientists (Kehoe et al., 2020). These conflicting interests lead to incoherence in policies which was identified as a major challenge for the governance of global supply chain sustainability (Newig et al., 2020). This policy incoherence can be either between different scales (e.g. state, national and global such as the World Trade Organization), or between consuming and producing countries (Cotta et al., 2022). Therefore, there should be more dialogue and negotiations between actors along global supply chains to align policy targets (e.g. 'what should be protected?') and agree on definitions of terms used in policies and agreements. This would then also help scientists to produce information that is consistent with the user needs and better able to support policy and monitor progress towards targets.

6.6 Conclusions

This thesis set out to understand opportunities to build on sub-national supply chain mapping data to support distant buyers of agricultural commodities with complex supply chains about environmental sustainability information in producing regions. Drawing from priorities identified in semi-structured interviews about the requirements of stakeholders, I used sub-national trade flow data, spatial data analyses and Life Cycle Assessment principles to estimate how the land and water used to produce agricultural commodities impacts LUC emissions, biodiversity damage, water scarcity and soil productivity loss at fine spatial scales. To respond to stakeholder needs I quantified the variability in those four impact categories in a consistent manner across the soy-producing countries of Brazil, Argentina and Paraguay in 2017. Results show a high spatial heterogeneity for all studied impact categories highlighting the need for traceability to municipality for robust impact assessments. Further findings show that geographic hotspots of LUC emissions have limited overlap with other studied environmental hotspots. For instance, while hotspots of LUC emissions are mostly located in the north and northeast of Brazil (Amazon and Cerrado), soil productivity loss and biodiversity damage are highest in southern Brazil whereas most regions highest in water scarcity are in Argentina. These differences between producing regions also affect which export countries have the largest footprints due to differences in countries' sub-national sourcing patterns. These findings illustrate the need to consider multiple dimensions of sustainability in corporate sourcing strategies and international trade agreements to identify and manage trade-offs. Additional research reveals that results were sensitive to methodological (e.g. land use change amortisation period) and data choices illustrating the need for additional consensus-finding by researchers and practitioners to allow enhanced comparison between reported estimates. Finding consensus will provide more accurate footprints overall, and avoid confusion of decision-makers or NGO representatives. Finally, incorporating sub-national supply chain mapping into predictive land use change models, improves the information provided from these models on where future land use change pressures will increase most, with potential implications for the prioritisation of efforts to protect natural land in discrete geographies or biomes.

In sum, this research makes a concrete contribution to improving 177iocon177lized177on within Life Cycle assessment and footprinting techniques, and to reduce existing uncertainties in estimates of land use and land use change impacts on greenhouse gas emissions, biodiversity and other ecosystem services such as soil productivity loss. It provides a platform for ongoing research that can continue to improve the knowledge about the consequences of international trade in agri-commodities on global sustainability. This has implications for policy and practice linked to forest-risk commodities such as soy. Future research should also seek to incorporate additional dimensions of sustainability so that trade-offs with social and economic aspects impacted by trade can be also identified and managed.

Supplementary Information

S.1 Supplementary Information Chapter 2

S.1.1 Research Ethics

Ethical approval has been received at the 20th of June 2019 by the Ethics Committee of the Environment and Geography Department confirmed through email by Dr Matthew Cotton.

S.1.2 Consent form

<u>Consent form for participants</u>

This form is for you to state whether or not you agree to take part in the study[23]. Please read and answer every question. If there is anything you do not understand, or if you want more information, please ask the researcher Carina Mueller (cmm563@york.ac.uk).

Have you read and understood the information leaflet about the study?	Yes ❒ No ❒
Have you had an opportunity to ask questions about the study and have these been answered satisfactorily?	Yes ❒ No ❒
Do you understand that the information you provide will be held in confidence by the research team, and your name or identifying information about you will not be mentioned in any publication unless we receive written permission to the contrary?	Yes ❒ No ❒
Do you understand that you may withdraw from the study at any time before the end of the data collection session without giving any reason, and that in such a case all your data will be destroyed?	Yes ❒ No ❒
Do you understand that the information you provide may be kept after the duration of the current project, to be used in future research on language?	Yes ❒ No ❒
Do you agree to take part in the study?	Yes ❒ No ❒
If yes, do you agree to your interviews being audio recorded? *(You may take part in the study without agreeing to this).*	Yes ❒ No ❒
Would you like to receive further information related to the project's findings and outcomes?	Yes ❒ No ❒

Your name (in BLOCK letters):____

Your signature: ____

Interviewer's name: Carina Mueller____

Date:____

[23] This research and the methods employed have received ethical approval from the Environment and Geography Department's Ethics Committee of the University of York.

S.1.3 Pre read material for interviews and interview questions

Information for Interviewees

Interactions in globalised supply chains: Linking demand for agricultural commodities to international environmental sustainability

This is a three-year PhD project by Carina Mueller (cmm563@york.ac.uk) supervised by Dr Chris West (Department of Environment and Geography, University of York), Prof Bob Doherty (Department of Management, University of York) and Karen Ellis from WWF. The project started in October 2018 and is funded by the Economic and Social Research Council (ESRC) Doctoral Training Partnership.

What is this research about and why is it important?

Globalisation of trade has created highly complex supply chains where the locations of agricultural production are often far upstream in the supply chain and outside of the direct control of manufacturing or retail companies. This distance and complexity are making it challenging to understand the environmental effects and risks of agricultural production. Increasing demand for agricultural commodities is driving the expansion of agriculture into tropical forests and other ecosystems.

Knowing exactly where a company is sourcing a commodity from, and the potential environmental risks and impacts associated with these, is currently often impossible, but new techniques are becoming available that will increasingly give companies this information, while at the same time there is growing interest of consumers to understand the environmental effects of their choices. Novel data and approaches on supply chain transparency and traceability combined with satellite-derived land use maps allow an improved understanding of the consequences of innovation and sourcing decisions on ecosystems in the supply chain. In particular, this new information allows us to link international trade to local regions of production where environmental impacts and risks manifest. Developing an understanding of environmental risk across multiple dimensions is needed to fully understand the consequences of changes to supply chains and the potential for trade-offs and unintended consequences on other components of the natural environment. However, even when such information is available, it is not yet clear how it can best be used in company decision-making. Developing a more holistic understanding of these issues is the focus of this research programme, that will incorporate and test a range of indicators such as those linked to greenhouse gas emissions, water resources, biodiversity and soil quality.

To ensure the methodologies and indicators developed in this PhD programme are useful for business decision-making, we will be conducting a series of interviews with industry representatives with the aim to understand the needs, priorities, challenges and opportunities of different organisations in the quantification of environmental risk and impacts in globalised supply chains driven by demand on agricultural commodities.

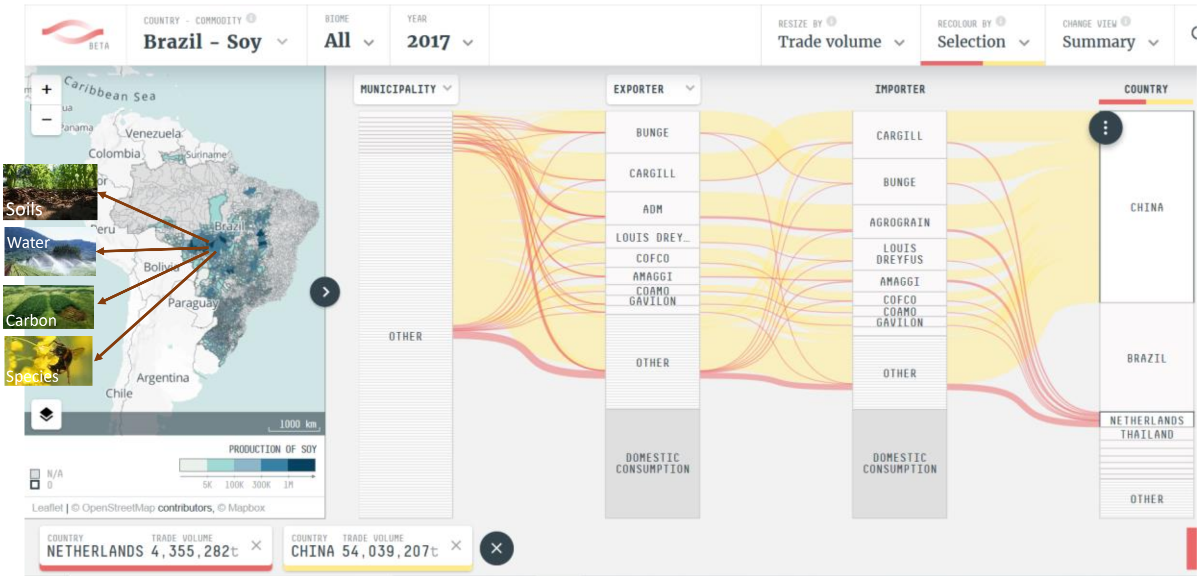

Figure S 1.1. Screenshot of Trase tool included in pre-read material for interviewees. Map of the geographical distribution of production linked through different exporters and importers to countries like China and the Netherlands (here as example soy in Brazil). This research aims to connect places of local production to environmental effects such as carbon, water and soils in the context of globalised agricultural supply chains.

What will participation involve?

Based on your valuable expert knowledge linked to this topic, you have been selected to contribute to this research project. If you would like to participate in our research, this would involve an interview taking around 30 to 60 minutes. During the interview you will be asked questions related to your organisation and its approach to consider the environmental sustainability of agricultural commodities. During the interview you can refuse to respond to any question. The interview can take place at the time and place of your convenience, such as at your office, a public place or a telephone or video call. If you are comfortable with it, we would prefer to record the interview to ensure everything you mention is captured correctly. Otherwise, if you prefer no audio recording, the183iocon183lher will take notes during the interview. The interviews will be carried out by Carina Mueller, a PhD student at the Stockholm Environment Institute at York. Prior to starting her PhD Carina has been working as an Environmental Sustainability Scientist for a consumer goods company contributing to the development and application of methodologies to provide better evidence of the long-term environmental sustainability for business decision-making. After the research has been completed, you will have access to research outputs partly or fully based on your interview transcripts. If relevant, you will be invited to workshops, public seminars or other events where the outcomes of this research will be presented. If you are interested to participate in further follow-up research such as a case study, this would also be possible.

How will anonymity be maintained?

All participants of interviews will remain anonymous unless we receive written confirmation to the contrary. We will also ask you to confirm whether or not you would like to remain anonymous at the start of the interview. All information shared by the participant such as email address or alternative address for correspondence (e.g. to check transcripts or share research outputs) will be stored by the researcher in accordance with the General Data Protection Act (2018). However, after you have confirmed that the interview transcripts are accurate, the transcripts will be anonymised. In case of using a quote from your interview in the research outputs, a generic description will be used (e.g. Retail industry representative 3). Unless we receive written permission to the contrary, any information that would allow to identify you (e.g. combinations of employer, job title and work place location) will be deleted from the transcript.

How long will the interview data be stored?

The aim is to store the anonymised and transcribed data together with the related consent forms for at least ten years after the project has finished (September 2021) in case the data are deemed useful for future research and publications. This is in line with the University of York guidelines. However, every two years the usefulness of the stored data would be revisited and if considered no longer needed, the data would be destroyed.

***What are the benefits of taking part?*[24]**

As an interviewee, you will receive early and priority access to outcomes of this research, and – if interested – an opportunity to have research outcomes presented to you and colleagues. Your contributions are intended to inform the research community in industry requirements and gaps in research that will improve interpretability and operability of potential impact and risk metrics and analysis, and the work of future research linked to the research team and the wider research community. This research makes a wider contribution to the development of supply chain decision support tools such as that of the Trase programme, which is supporting efforts to reduce deforestation and other ecosystem-risks in agricultural supply chains. Additionally, it is our intention to seek case studies to apply methods and act as pilots for the use of this information in decision making in retail and consumer-goods manufacturing settings. After the initial interview, if you wish, we will invite you to stay engaged and/or become an early adopter within one such case study.

Is it possible to withdraw the participation? What happens then?

It is possible to withdraw the participation from the study if you would like to do so without any repercussions. In this case your transcribed interview would be destroyed and all related information excluded from the research. However, as the information you will have given could be cited in written or oral form during the process of this research, such as in published articles of scientific journals, it is recommended to notify us of your withdrawal at the latest four months after the interview took place.

What next?

If you would like to take part in an interview for this research, I will follow-up by email or telephone to make arrangements for the interview, so that a suitable date and location can be arranged. Just before the interview, the aims of the study will be explained to you again and you will have the chance to ask any questions. After this, you would need to sign a consent form confirming that you agree to participate in this research. If you have any further questions before the interview, please do not hesitate to contact us.

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[24]

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S.1.4 Interview Protocol

Table S 1.1. Indicative questions of semi-structured interviews and focus group discussions.

1. Pre-interview checks	Timing

• Thank you very much for taking the time and agreeing to share your understanding.
• Purpose of interview:
    o Understand motivations of organisations to make commitments and take actions on global environmental sustainability.
    o Understand currently used tools, methodologies and data to understand environmental sustainability in supply chains.
    o Explore actor's perspective on methodological gaps to understand environmental sustainability in traceable/transparent supply chains.
• Length: 30-60 minutes
• Check that participant has read the information sheet and signed the consent form.
• Check if participant is happy for the interview to be recorded.
• Check if participant has any questions before we start the interview.
• Check if participant or his organisation would like to stay anonymous.
	2 minutes

2. Warm-up phase	
• Identify a unique identifier – ask for initials and favourite number • What is your background and what is your current role in the organisation? • How many years have you already been working for this company and in this role?	5 minutes
3. Definitions/Language	
• Which terms or frameworks do you use in your organisation most frequently to talk about global environmental sustainability? Could you explain why and discuss? • What is your understanding of the term Natural Capital as used in your organisation?	10 minutes
4. Motivation	
• What are the factors that motivate your organisations to make commitments and take actions that affect your agricultural supply chain? Which factors, if any, are holding you back?	10 minutes
5. Concerns	

• What are your organisation's biggest concerns related to the long-term environmental sustainability/Natural Capital in your supply chains?	5 minutes
6. Opportunities	
• What are the opportunities for your organisation to take action and improve the environmental sustainability within your supply chain? • Do you think these have changed over time? And if yes, why?	5 minutes
7. Actions	
• Which actions or decisions are you planning to take to meet your commitments or tackle the concerns? • Is it about changing the current system or preparing your business for the future?	5 minutes
8. Current use of information	
• Which methodologies, tools and data are you currently using to understand the environmental sustainability in your globalised supply chains? • How do you measure progress towards your commitments? Which data are you using for this? Are you engaging with your suppliers to get better data? What is the spatial resolution at the environmental risk/impact side? • Which metrics or indicators are you currently using? • Are you more interested in understanding risks or potential impacts? And why?	5 minutes
9. Future needs on information	
• How could these tools incorporating supply chain risks and potential impacts be made more relevant and applicable to inform (strategic) decisions in your organisation? • Which indicators or metrics are missing from your perspective? • What would be your criteria to select methods/tools? How important would it be that they are globally and -consistently available across commodities and geographies? • What would be an appropriate resolution/scale for you?	10 minutes
10. Wrap-up	
• From your perspective, is there anything else you would like to add about how science on environmental sustainability can be improved to inform your decisions? • I will send you the transcript of your interview shortly so that you have a chance to double-check if I understood everything correctly. • Thank you so much for your time again.	Chapter 3 minutes

S.1.5 Themes and codes

Table S 1.2. Overview of themes and codes

Themes	Codes
Motivations	Be seen as leader in sustainability
	Doing the right thing
	Security of supply agricultural commodities in future under scarce resources and climate change
	Foreseeing what consuming governments might ask of companies in future
	Following what NGOs recommend
Specific sustainability concerns	Use of different frameworks to identify which sustainability concerns matter (e.g., Natural Capital, planetary boundaries, ecosystem services)
	Help wanted from experts what they should care about
	Mentioned biodiversity, water, ecosystem conversion, greenhouse gas emissions, soils, land use, deforestation.
Type of actions/decisions	Certification unable to tackle problem for commodities with complex supply chains
	Improve traceability and transparency of supply chains
	Help needed on which actions will be most effective
	Improve farming practices
	Jurisdictional/landscape approaches
	Collaboration with others to affect change
	More 'sustainable sourcing'
Unintended consequences Limitations of existing methods/tools	Social impacts
	Challenge to understand full system and its consequences Balancing simplicity with complexity
	Balancing global coverage vs local specificity
	Would like to consider multiple concerns together
	Lack of good quality data
	Lack of data at high spatial resolution
	Lack of timely/recent data
	Scientists do not agree on indicators leading to confusion
	High level of uncertainty for some geographies or indicators
Barriers to implementation	Complexity of Supply chain as barrier to action
	Available traceability and transparency data have a time-lag
	Perceived power to affect meaningful change 'at scale'
	Lack of in-house capacity
	False beliefs leading to in-action
	Lack of incentives for farmers on ground to change practices
	Some solutions too costly such as traceability to farm

Table S 1.3. Range of opinions on the level of appreciated complexity among different types of stakeholders as illustrated in selected citations.

Actor type	Complexity
Manufacturer	*"So a tool, if it only did greenhouse gas calculations and land use change, then that might be fine for some, but the more that it can do on top of that the better probably." (M2)*
Retailer	*"If we make it too complex [multiple indicators], then we don't do anything, we don't dare to do anything. But I think we are entering from that simplification era to actually go into and acknowledge that this is a complex situation. [...] I do think that there is a lot of here, there is a lot more need for research guidance" (R4)*
NGO	*"I mean ideally absolutely we want people to look at all of these metrics [...] but it gets very complicated [...]. So, what we need is enough data that guides companies in the right direction without bogging them down in detail, right?" (NGO4)*
Consultant	*"When we use GHG reduction as the sole, or deciding, indicator of a sustainable food system, it leaves us at risk of failing to address other critical aspects of food system sustainability. Soil health and biodiversity are key metrics gaps towards achieving the desired outcome of sustainable food systems." (C3)*
Certifiers	*"I would say try to avoid too comprehensive analyses – it is not worth the effort as there is so much uncertainty" (CB3)*
Scientific expert	*"I like to joke that the Anthropocene, is really the ANDthropocene – that we need to be much better about recognizing the impacts of food on health AND hunger AND water AND biodiversity AND land AND climate. We're not there yet and I find that people are unable to understand multiple issues and their interactions." (Scientific Director, EAT Lancet)*

S.2 Supplementary Information Chapter 3

S.2.1 ESA CCI Land Cover Classification

Table S 2.1. Overview of the ESA CCI Land Cover Classes. Definitions of the CCI land use (LU) classes (UCL Geomatics, 2017) as prevalent in countries analysed in this study

ESA LU code	Definitions of land cover class
10, 11, 12	Rainfed cropland
20	Irrigated cropland[a]
30	Mosaic cropland (>50 %)/ natural vegetation (tree, shrub, herbaceous cover) (<50 %)[b]
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50 %)/ cropland (<50 %)[b]
50	Tree cover, broadleaved, evergreen, closed to open (>15 %)[d]
60, 61 , 62	Tree cover, broadleaved, deciduous, closed to open (>15 %) [d]
70, 71, 72	Tree cover, needleleaved, evergreen, closed to open (>15 %) [d]
90	Tree cover, mixed leaf type (broadleaved and needleleaved) [d]
100	Mosaic tree and shrub (>50 %)/ herbaceous cover (<50 %)[c]
110	Mosaic herbaceous cover (>50 %)/ tree and shrub (<50 %)[c]
120, 121, 122	Shrubland
130	Grassland
150, 151, 152, 153	Sparse vegetation (tree, shrub, herbaceous cover) (<15 %)
160	Tree cover, flooded, fresh or brakish water [d]
170	Tree cover, flooded, saline water [d]
180	Shrub or herbaceous cover, flooded, fresh/saline/brakish water
190	Urban areas
200, 201, 202	Bare areas
210	Water bodies

[a]cropland classes; [b]mosaic agriculture classes; [c]mosaic tree, shrub and herbaceous cover classes; [d]forest classes

S.2.1 Land cover change considered as cropland expansion

I excluded conversion to mosaic class 30 (Mosaic cropland (>50 %)/ natural vegetation (tree, shrub, herbaceous cover) (<50 %)) and mosaic class 40 (Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50 %)/ cropland (<50 %)) and only analysed conversion to pixels that were 100 % cropland (i.e. classes 10,11, 12 and 20). This follows Eigenbrod et al. (2020) who also excluded these land cover classes and considered ESA CCI land cover class 30 and 40 to be smallholder agriculture or slash and burn agriculture. The following land cover conversion types were considered to be attributable to cropland expansion: i) natural land (i.e. ESA CCI Land cover classes 30-210) to cropland and ii) the mosaic land (class 30 and 40) to cropland.

S.2.2 Carbon stocks estimation

Changes in the stocks of carbon on natural land (Eq. 1) which are released to the atmosphere following land conversion to soybeans as greenhouse gas emissions (GHG) GHG_{LUC} (Eq. 2) in t CO_2 eq. ha^{-1} yr^{-1}were calculated as follows (Lam et al. 2021):

$$\boldsymbol{CS = C_{AG,j} + C_{BG,j} + CS_{Soil,j}} \quad \text{(Equation 3)}$$

$$\boldsymbol{GHG_{LUC,j} = \frac{CS_{j,t0} - CS_{j,tAP}}{AP} * \frac{44}{12} * t_{occ}} \quad \text{(Equation 4)}$$

Where C_{AG} is Aboveground-, C_{BG} Belowground and C_{Soil} the Soil carbon stocks (in t C ha^{-1}) in each soybean harvested pixel *j* at time *t*; *AP* the amortisation period for annualising LUC emissions and t_{occ} is the duration of the occupation process (i.e. 1 if single-cropped and 0.5 if double-cropped), following Lam et al (2021). While I assumed that above and belowground carbon is zero after conversion to soybeans as it is an annual crop (Lam et al. 2021), the loss in soil carbon was calculated following Esteves et al. (2016) who provide soil carbon loss factors depending on the farming practices and the previous land cover.

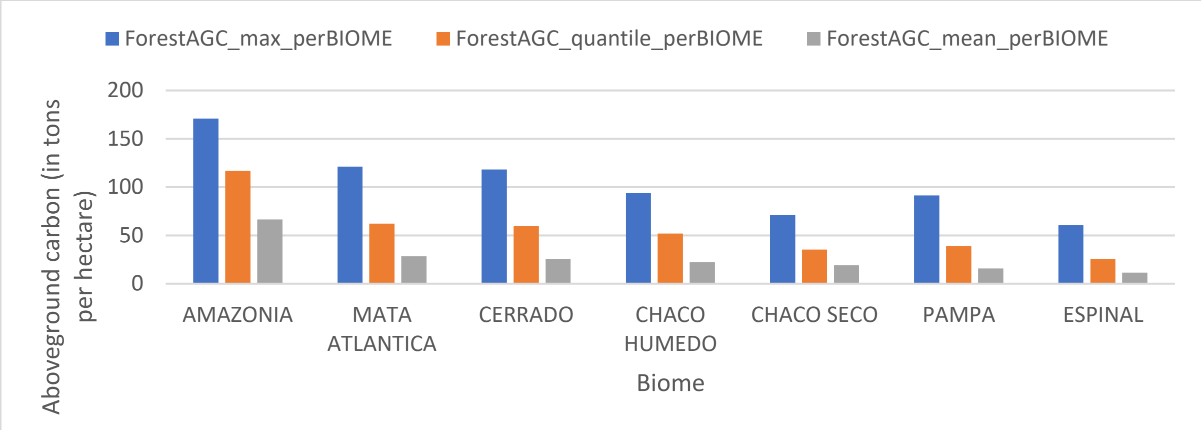


Figure S 2.1. Comparison of mean for each biome of maximum, 90th quantile and mean aboveground carbon of each municipality

The total land use change emissions are then estimated for each municipality as (Eq.5):

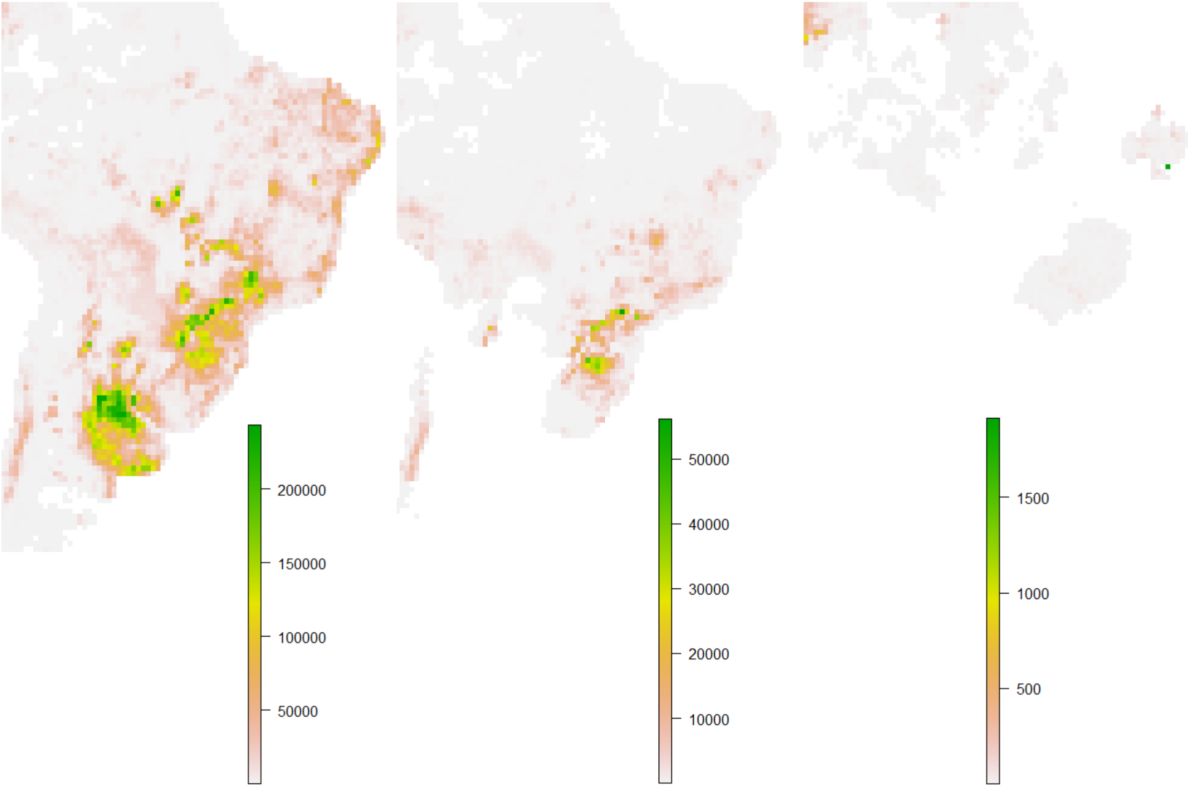
$$GHG_{LUC_{i,j,m}} = \sum_j A_{Trans_{i,j}} \times CS_{i,j} \qquad \text{(Equation 5)}$$

Where A_{Trans} is the transformed area for each land cover type *I* and pixel *j* over which the land use change is amortised (i.e. 20 years in the base case) per soy tonne within each municipality *m*.

I assumed carbon density to be consistent across each land cover class within the biome. To date only emissions from aboveground carbon were considered though this could be expanded to include belowground (i.e. roots) and soil carbon as well following Escobar et al. (2020).

Table S 2.2. Aboveground carbon stock values used in tons carbon per hectare (Source: CDIAC Table S1a-f)

			Ecofloristic zones			
ESA land use code			**Tropical rainforest**	**Tropical Moist Deciduous Forest**	**Subtropical humid forest/steppe**	**Tropical Dry Forest**
	Biomes		**Atlantic Forest, Mato Grosso Dry Forest, Parana Paraiba Interior Forest**	**Humid Chaco**	**Espinal, Humid Pampas, Araucaria Forest**	**Dry Chaco**
50,60, 70, 80, 160, 170	Tree cover >15 %	Forest	193	128	128	126
30	Mosaic cropland (>50 %)/ natural vegetation (tree, shrub, herbaceous cover) (<50 %)	Mosaic of Agriculture	96.5	64	64	63
40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50 %)/ cropland (<50 %)					
100	Mosaic tree and shrub (>50 %)/ herbaceous cover (<50 %)	Mosaic of Natural Land	96.5	64	64	63
110	Mosaic herbaceous cover (>50 %)/ tree and shrub (<50 %)					
120, 121,122	Shrubland	Shrubland	53	53	50	53
130	Grassland	Grassland	8	8	8	4
190	Urban areas	Rest	4	44	44	4
200, 201, 202	Bare areas					
210	Water bodies					



Single-cropped area (in hectare per pixel)

Double-cropped area (in hectare per pixel)

Triple-cropped area (in hectare per pixel)

Figure S 2.2. Area single, double or triple-cropped in hectare per pixel with any crop 1998-2002.

S.2.3 Biodiversity Characterization Factors

Occupation impacts (*OI*) can be derived as:

$$\boldsymbol{OI_{LU_j} = \left(A_{Occ_{i,r}} \times t_{Occ_r}\right) \times CF_{Occ,LU_r}} \qquad \text{(Equation 6)}$$

Where A_{Occ} is the occupied area, t_{Occ} the duration of the occupation process and CF_{Occ} the Characterization Factor for occupation for each land use *l* and ecoregion *r* (Koellner et al. 2012). Transformation impacts (*TI*) are estimated following

$$TI_{Ref\rightarrow LU_{i,j}} = A_{Trans_{i,j}} \times CF_{Trans_{i,j}}$$

$$= \boldsymbol{\frac{1}{2} \times A_{Trans_{i,j}} \times CF_{Occ,LU_{i,j}} \times t_{reg_{i,j}} \times t_{Occ,LU}} \qquad \text{(Equation 7)}$$

with the transformed area A_{Trans} and the time t_{reg} an ecosystem requires to regenerate to the quality of the pristine habitat after a disturbance (Koellner et al. 2012). The total Biodiversity Damage

Potential (BDP_{total}) of land use can then be calculated as the sum of the transformation impact (*TI*) and the occupation impact (*OI*) over all land use types *l* and ecoregions *k* (Koellner and Scholz 2007):

$$\boldsymbol{BDP_{total}} = \sum \boldsymbol{TI_{Ref \rightarrow LU_{i,k}}} + \sum \boldsymbol{OI_{LU_{i,k}}} \quad \text{(Equation 8)}$$

S.2.4 Biodiversity Characterization Factors per Biome

Table S 2.3. Overview of Characterization Factors used (Source: Chaudhary and Brooks, 2018, names of ecoregions (eco) from The Nature Conservancy)

eco_code	TRASE_BIOME NAME	CHAUDHARY_ECOREGION NAME	CF_Occ_Int_crop	CF_Trans_Int_crop
NT0704	BR-CERRADO	BR-CERRADO	1.10E-13	6.92E-12
NT0708	AR-CHACO HUMEDO	AR-HUMID CHACO	1.04E-13	6.57E-12
NT0210	AR-CHACO SECO	AR-CHACO	1.00E-13	6.41E-12
NT0801	AR-ESPINAL	AR-ARGENTINE ESPINAL	6.30E-14	8.90E-12
NT0150	PY-MATA ATLANTICA	PY-ALTO PARANA ATLANTIC FOREST	3.88E-13	3.31E-11
NT0803	AR-PAMPA	AR-HUMID PAMPAS	7.91E-14	1.12E-11
NT0804	BR-PAMPA	BR-HUMID PAMPAS	7.91E-14	1.12E-11
NT0704	BR-AMAZONIA	BR-CERRADO	1.41E-13	9.12E-12
NT0212	BR-AMAZONIA	BR-CHIQUITANO DRY FORESTS	1.75E-13	1.58E-11
NT0135	BR-AMAZONIA	BR-MADEIRA-TAPAJOS MOST FOREST	1.98E-13	1.70E-11
NT0140	BR-AMAZONIA	BR-MATO GROSSO SEASONAL FOREST	1.07E-13	9.12E-12
NT0170	BR-AMAZONIA	BR-TOCANTINS/PINDARE MOIST FOREST	1.64E-13	1.40E-11
NT0202	BR-MATA ATLANTICA	BR-ALTO PARANA ATLANTIC FOREST	1.99E-13	1.78E-11
NT0101	BR-MATA ATLANTICA	BR-ARAUCARIA MOIST FOREST	4.89E-13	4.14E-11
NT0704	BR-MATA ATLANTICA	BR-CERRADO	1.41E-13	9.12E-12
NT0710	BR-MATA ATLANTICA	BR-URUGUAYAN SAVANNA	1.48E-13	9.35E-12

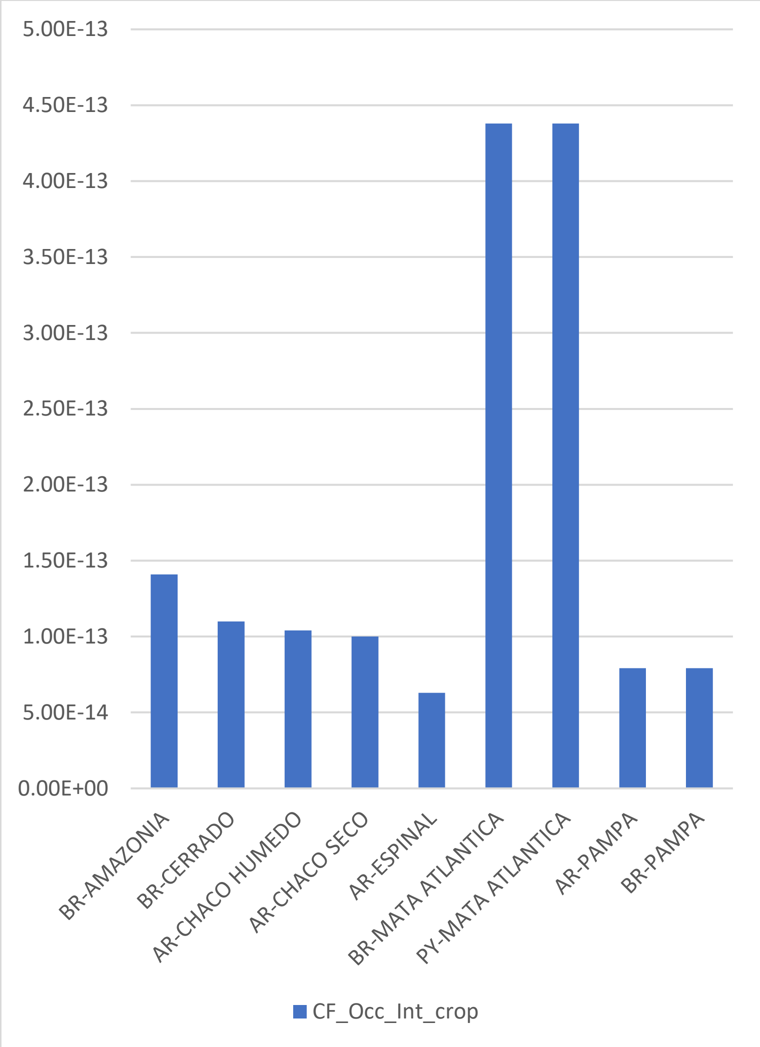


Figure S 2.3: Characterization Factors for Global Species Loss

S.2.5 Calculation of Biodiversity Damage Potential

The total Biodiversity Damage Potential (BDP_{total}) of land use can be calculated as the sum of the transformation impact (*TI*) and the occupation impact (*OI*) over all land use types *l* and ecoregions *k* (Koellner and Scholz 2007):

$$BDP_{total} = \sum TI_{Ref \rightarrow LU_{i,k}} + \sum OI_{LU_{i,k}} \tag{5}$$

Transformation impacts (*TI*) are estimated following

$$TI_{Ref \rightarrow LU_{i,j}} = A_{Trans_{i,j}} \times CF_{Trans_{i,j}}$$

$$= \frac{1}{2} \times A_{Trans_{i,j}} \times CF_{Occ,LU_{i,j}} \times t_{reg_{i,j}} \times t_{Occ,LU} \tag{6}$$

with the transformed area A_{Trans} and the time t_{reg} an ecosystem requires to regenerate to the quality of the pristine habitat after a disturbance (Koellner et al. 2012).

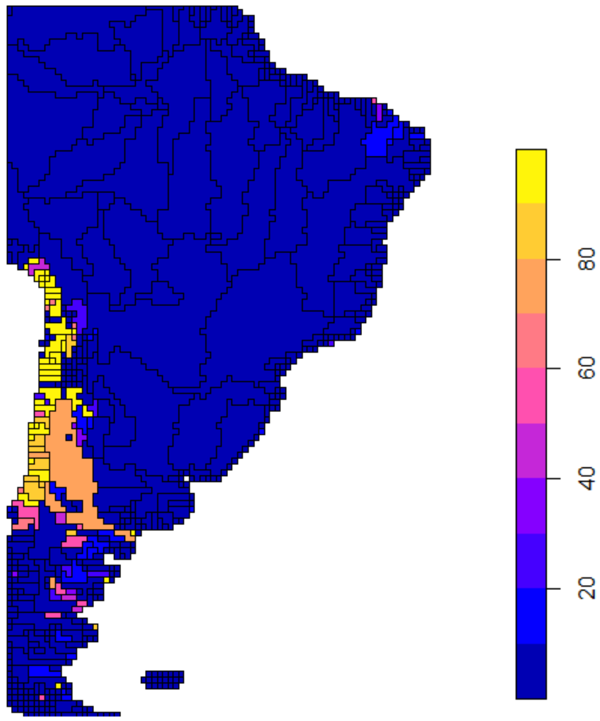


Figure S 2.4. AWARE Water Scarcity Indicator for agricultural use for each watershed in Argentina, Brazil and Paraguay (data from Boulay et al. 2018) ranging for this case study between 0.2 (green) and 21.0 (red) m3 world eq.

S.2.6 Additional results

The difference in sourcing patterns affected which environmental impact was largest for each consuming country.

Table S 2.4. Share of area converted from natural land to soybean harvested area in 2017

Producing Country	BIOME	Share Converted in past 20 years
Brazil	AMAZONIA	65.5 %
Brazil	PAMPA	26.5 %
Brazil	CERRADO	20.0 %
Brazil	MATA ATLANTICA	15.6 %
Argentina	CHACO SECO	42.0 %
Argentina	CHACO HUMEDO	33.1 %
Argentina	ESPINAL	8.4 %
Argentina	PAMPA	7.2 %

Producing country's biodiversity impacts were mostly affected by their different trade patterns (Figure S 2.5). Countries with large potential biodiversity damage per unit of soy import are France (14.03 x 10^{-10} PDF $tonne^{-1}$), Brazil (14.27 x 10^{-10} PDF $tonne^{-1}$) and South Korea (12.9 x 10^{-10} PDF tonne $^{-1}$) whereas the smallest impacts on biodiversity had Indonesia (6.84 x 10^{-10} PDF $tonne^{-1}$), Vietnam (5.17 x 10^{-11} PDF $tonne^{-1}$) and Egypt (3.89 x 10^{-11} PDF $tonne^{-1}$) (Figure 3.6c). The latter had less than half of the impacts of the country with the largest impacts.

Linking producing regions to importers, the five largest soil erosion CFs among the 15 largest soy consumers in 2017, are determined for Brazil (0.24 % $tonne^{-1}$), South Korea (0.20 % $tonne^{-1}$), France (0.18 % $tonne^{-1}$), China (0.17 % $tonne^{-1}$) and Netherlands (0.15 % $tonne^{-1}$) (Figure 3.7d). Brazil, the second largest soybean consumer, has a CF almost ten times higher than the smallest CF of the countries I considered – for Egypt. For Brazil, 64 % of embedded soil erosion impacts are associated with three states: Goias, Parana and Rio Grande do Sul.

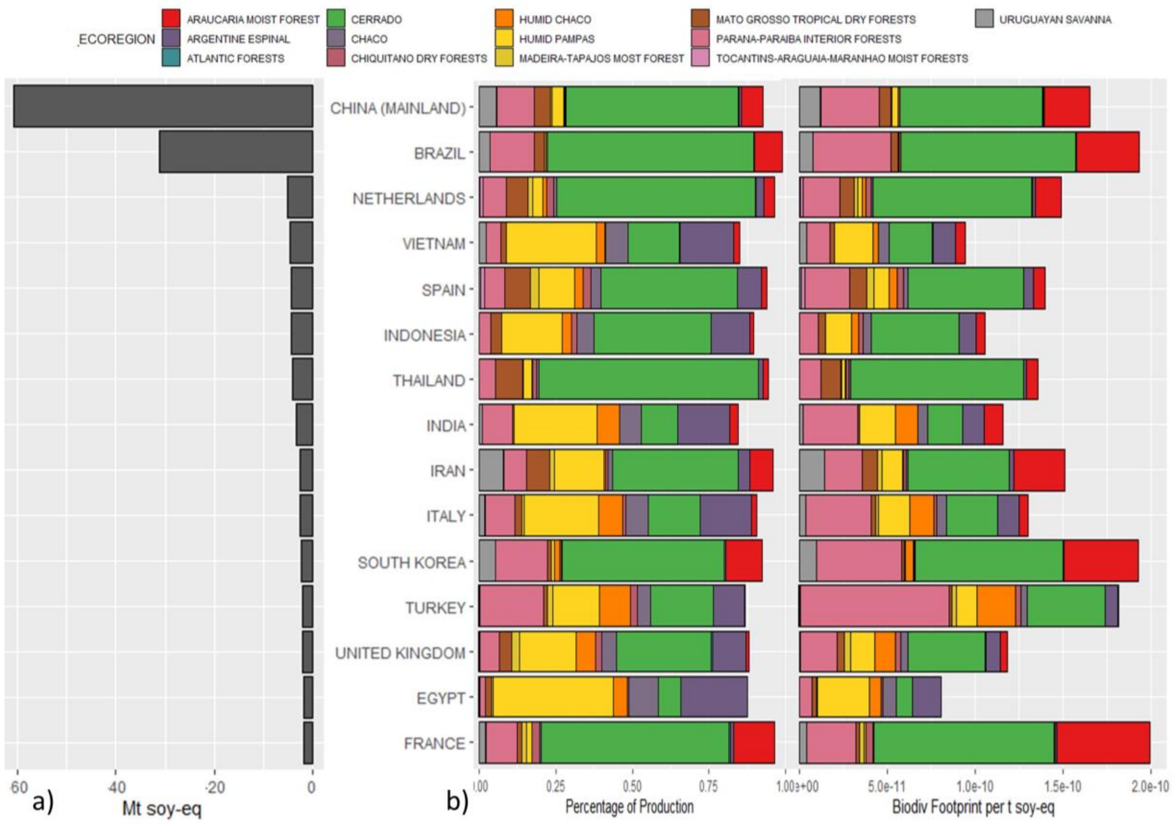


Figure S 2.5: The total import quantities of soybeans including derivatives such as cake and oil (a). Ecoregion origin of major soybean importers from Argentina (AR), Paraguay (PY) and Brazil (BR) (b).

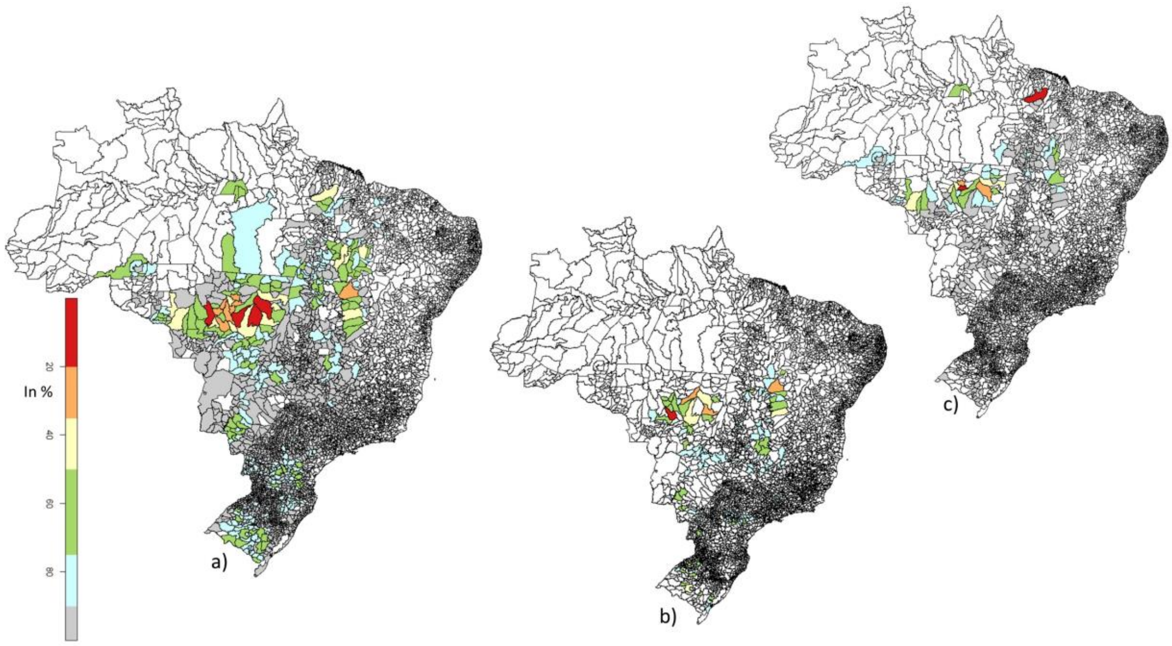


Figure S 2.6. Proportional cumulative land use change emissions per soy tonne in Brazil for a) all consuming countries together, b) only Vietnam and c) only Spain. The colours illustrate the contributing share to the overall land use change emissions.

Table S 2.5. Comparison of LUC emissions aggregated from municipality to state by using the soy commodity mix compared to equal weighting of each municipality

COUNTRY	STATE_ID	LUC emissions in tonne per tonne [Commodity weighted]	LUC emissions in tonne per tonne [Non-Commodity weighted]
BRAZIL	BR-PARA	3.53	2.90
BRAZIL	BR-RONDONIA	2.58	2.69
BRAZIL	BR-PIAUI	2.07	2.51
ARGENTINA	AR-SALTA	1.81	1.70
BRAZIL	BR-MATO GROSSO	1.79	1.12
BRAZIL	BR-MARANHAO	1.68	2.18
BRAZIL	BR-TOCANTINS	1.59	1.81
PARAGUAY	PY-CAAZAPA	1.19	1.18
ARGENTINA	AR-CHACO	1.15	0.99
PARAGUAY	PY-ITAPUA	0.96	0.94
PARAGUAY	PY-CAAGUAZU	0.85	0.92
PARAGUAY	PY-CANINDEYU	0.83	0.77
BRAZIL	BR-SANTA CATARINA	0.80	0.87
BRAZIL	BR-BAHIA	0.77	0.61
ARGENTINA	AR-ENTRE RIOS	0.74	0.87
ARGENTINA	AR-SANTIAGO DEL ESTERO	0.74	0.96
PARAGUAY	PY-ALTO PARANA	0.71	0.63
PARAGUAY	PY-SAN PEDRO	0.68	0.67
BRAZIL	BR-RIO GRANDE DO SUL	0.37	0.53
BRAZIL	BR-PARANA	0.34	0.21
BRAZIL	BR-MATO GROSSO DO SUL	0.32	0.17
ARGENTINA	AR-BUENOS AIRES	0.24	0.15
BRAZIL	BR-SAO PAULO	0.19	0.11
BRAZIL	BR-MINAS GERAIS	0.12	0.08
BRAZIL	BR-GOIAS	0.11	0.06
ARGENTINA	AR-LA PAMPA	0.10	0.10
ARGENTINA	AR-SANTA FE	0.06	0.06
ARGENTINA	AR-CORDOBA	0.02	0.02

S.3 Supplementary Information Chapter 4

S.3.1 Carbon stocks

Table S 3.1. Carbon stocks in forest land cover aggregated for each studied biome and producing country (estimated from Santori et al 2021 dataset).

Producing Country	BIOME	Carbon stocks in ton per hectare
Brazil	Amazon	105.0
Brazil	Cerrado	47.8
Brazil	Mata Atlantica	45.7
Paraguay	Mata Atlantica	44.4
Brazil	Pampa	38
Argentina	Chaco Seco	36.7
Argentina	Humid Chaco	31.3
Argentina	Espinal	24.3
Argentina	Pampa	23.9

Table S 3.2. Alternative data sources used for above- and belowground carbon (ABGC) (source: Ruesch and Gibbs, 2008)

FAO Ecofloristic Zone	Land Cover Class	ABGC (ton per ha)
Tropical rainforest	Forest	193
Tropical moist deciduous forest	Forest	128
Subtropical humid forest	Forest	128
Tropical dry forest	Forest	126

S.3.2 Supplementary Results

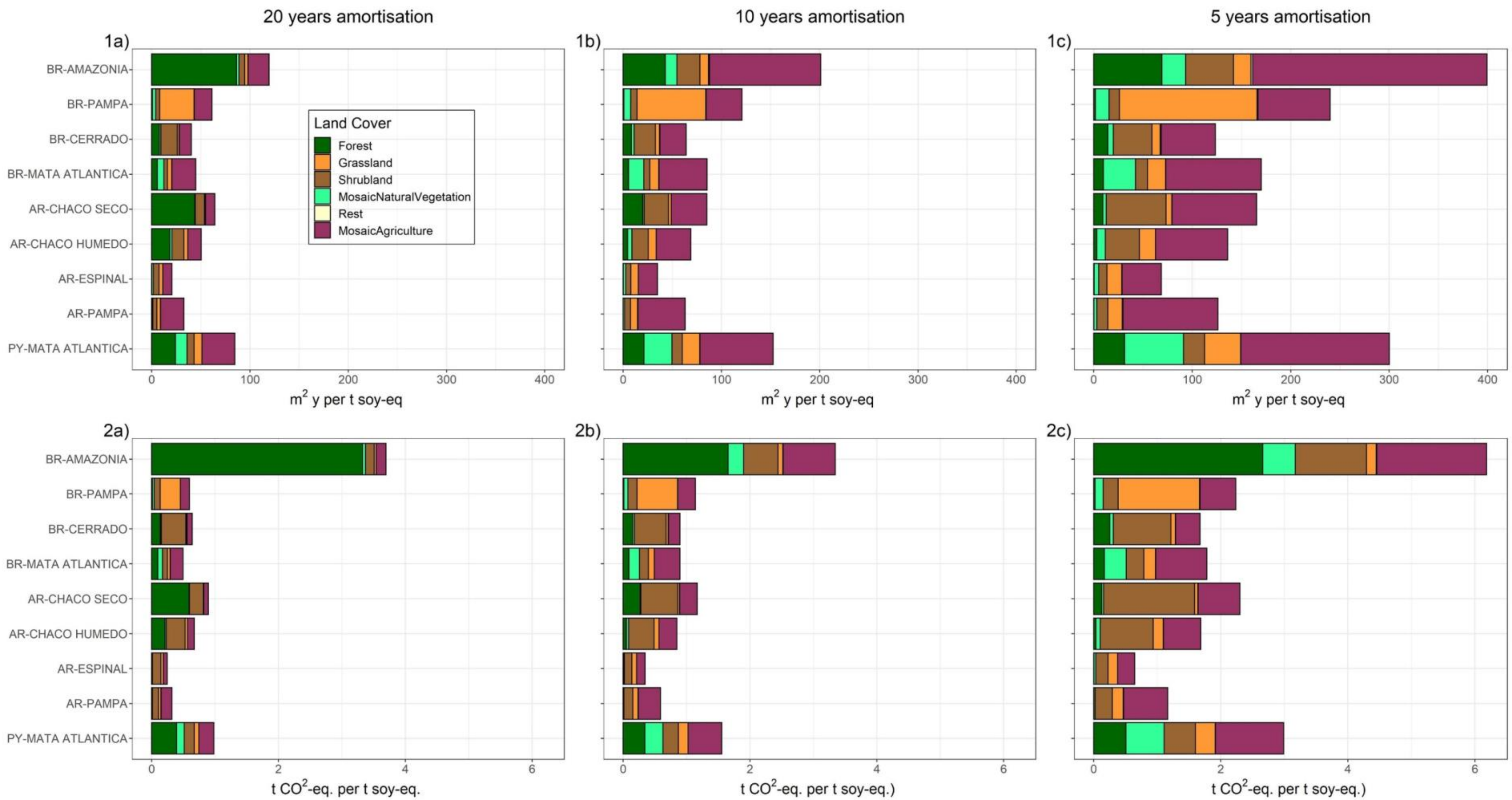


Figure S 3.1: Sensitivity to different amortisation time periods: 20 years (1996-2016) a), 10 years (2006-2016) b) and 5 years (2011-2016) c) affecting land transformation (life cycle inventory) of the soy producing biomes in countries 1), as m^2 per soy-eq; and resulting potential land use change emissions 2), as CO_2 per soy-eq. (t t^{-1}). Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. Biomes are ordered within each country by decreasing land conversion area over 20 years allocation excluding Mosaic of agriculture land cover type

S.3.3 Land conversions aggregated per biome

Table S 3.3. Comparison of share converted from Natural Land (classes 50-210) for each biome in Brazil (BR), Argentina (AR) and Paraguay (PY) (Source: output of Google Earth Engine overlaying ESA CCI land cover with soybean raster from (Song et al., 2021))

	Share Natural Land before soybean sowing in %		
Biome	20 years before	10 years	5 years before
BR-AMAZONIA	65.5	29.3	26.9
BR-PAMPA	26.5	25.8	25.5
BR-CERRADO	20.0	13.3	12.1
BR-MATA ATLANTICA	15.6	13.9	13.9
AR-CHACO SECO	18.9	18.9	15.3
AR-CHACO HUMEDO	15.2	15.2	14.2
AR-ESPINAL	5.8	5.8	5.4
AR-PAMPA	6.0	6.0	5.9
PY-MATA ATLANTICA	33.1	25.3	24.2

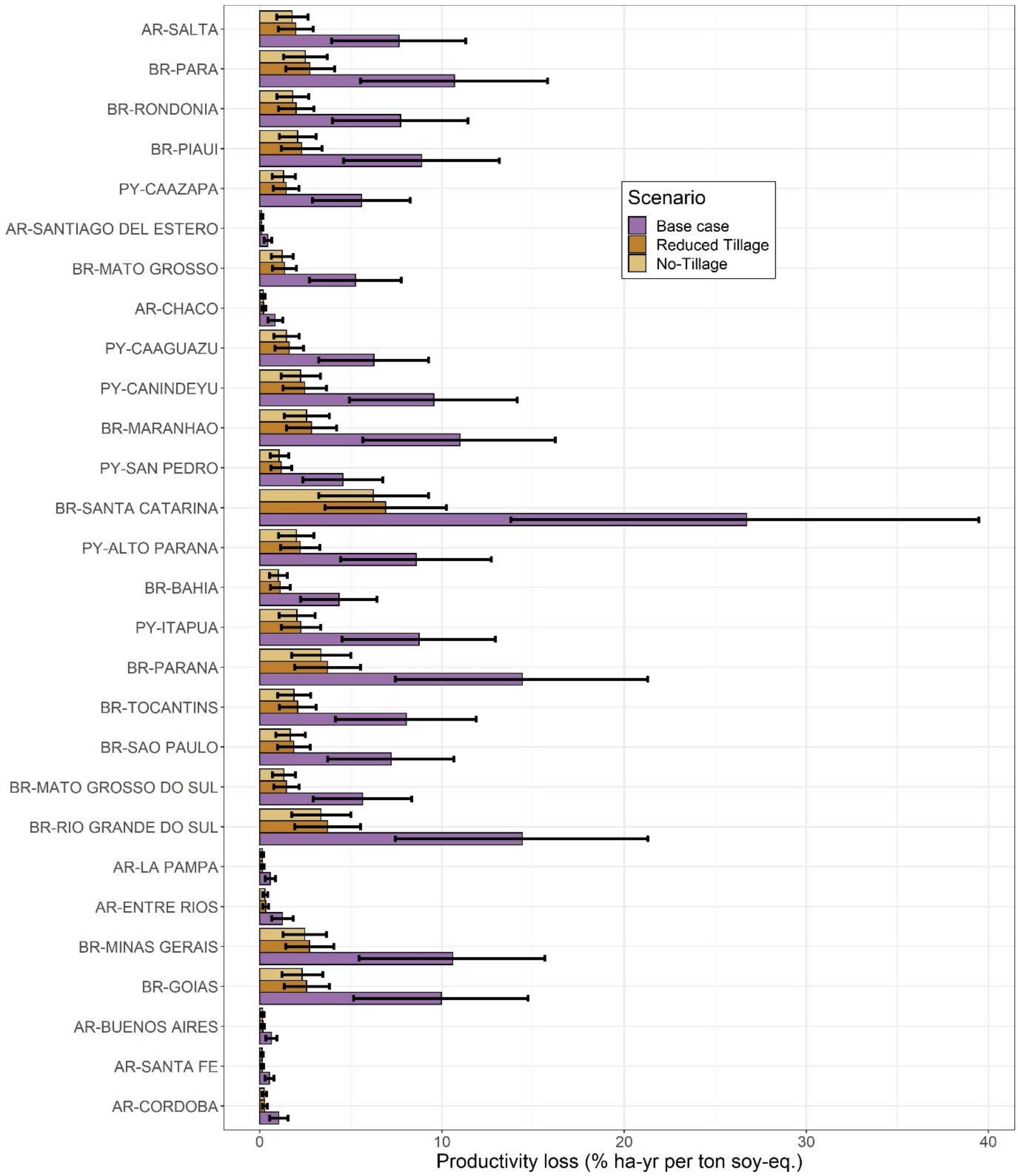


Figure S 3.2: Soil productivity loss due to water erosion depending on tillage practice for one tonne of soybean produced in 2017. Error bars illustrate the uncertainty in the conversion of soil erosion to productivity loss. Country names were abbreviated with BR = Brazil, AR = Argentina, PY = Paraguay. States are ordered within each country by decreasing land conversion area over 20 years allocation excluding Mosaic of agriculture land cover type.

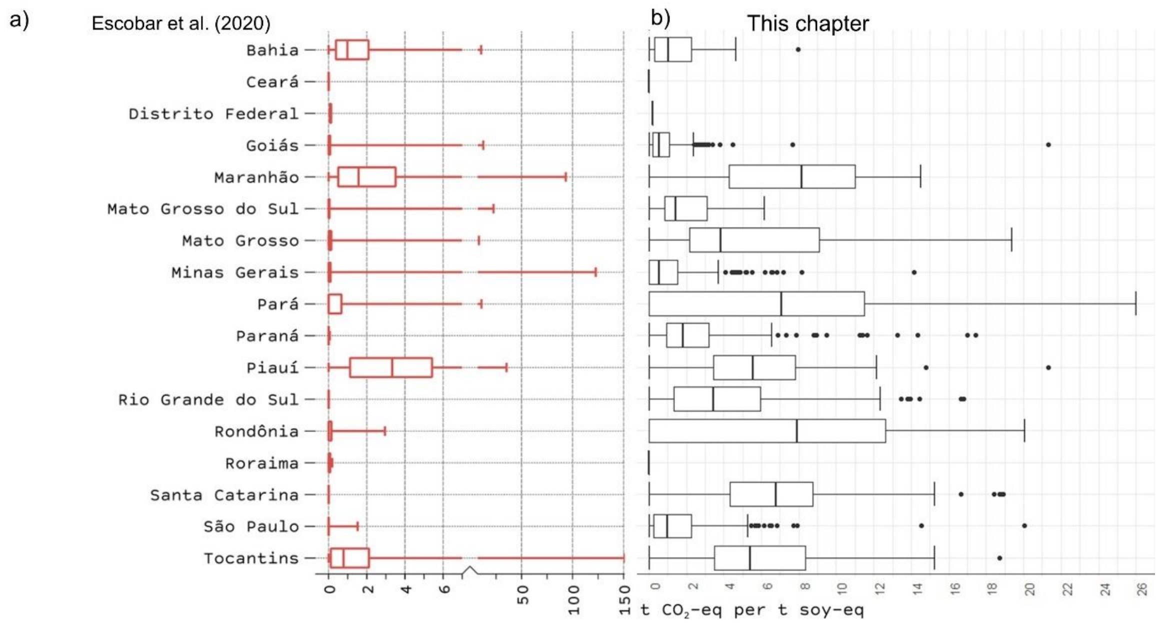


Figure S 3.3: Greenhouse gas emissions from LUC of Brazilian soy at the level of states and country in related studies using a Life Cycle Assessment approach (a) and results compared from this Chapter using a five year amortisation period (b). Variability in Escobar et al. (2020) and this chapter is the range of municipality-level LUC emissions for each state within Brazil.

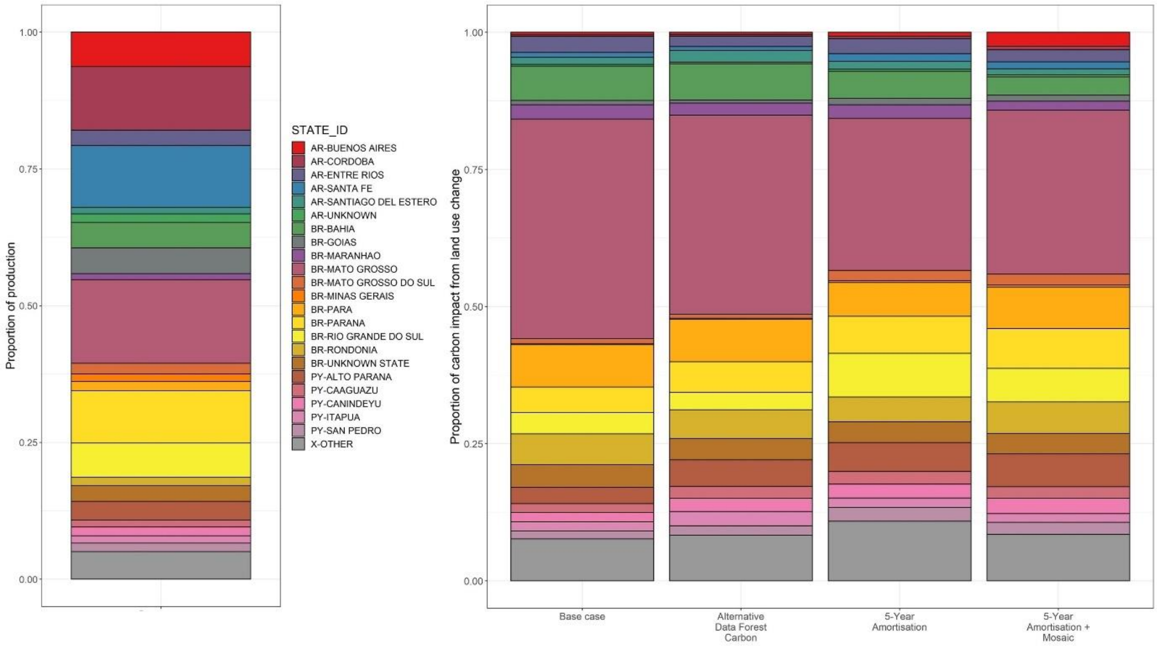


Figure S 3.4: Comparison of soy-induced LUC emissions for the EU depending on different sensitivity choices. Each bar illustrates the proportion of the total LUC emissions related to soybean production of each state within the three producing countries Brazil (BR), Argentina (AR) and Paraguay (PY).

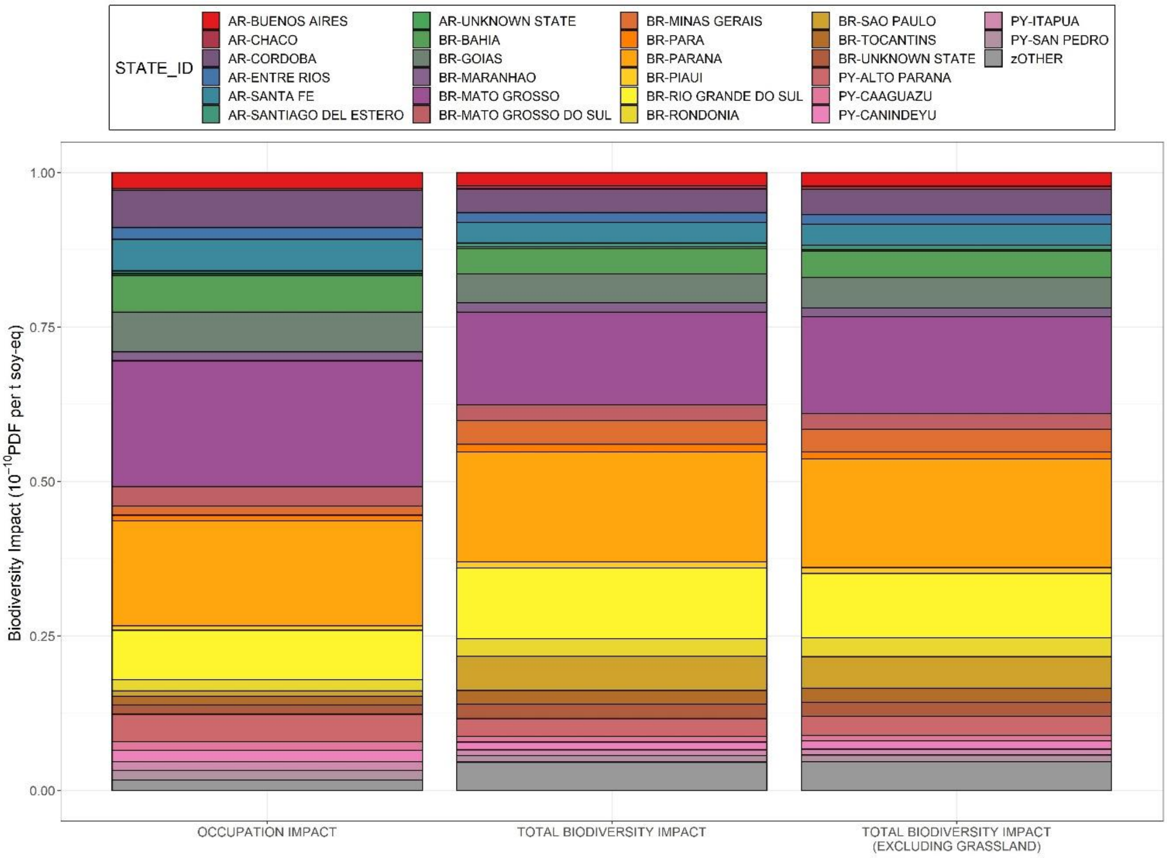


Figure S 3.5: Comparison of biodiversity damage of soybean consumption for the EU depending on different sensitivity choices. Each bar illustrates the proportion of the total biodiversity damage related to soybean production of each state within the three producing countries Brazil (BR), Argentina (AR) and Paraguay (PY).

Abbreviations

AGB	Aboveground Biomass
AGC	Aboveground Carbon
AP	Amortisation Period
AR	Argentina
AWARE	Available Water Remaining
BR	Brazil
CF	Characterization Factor
CF_Occ_Int_crop	Characterisation Factor for Occupation with Intensive Crop
CO	Conversion factor
EC	European Comission
EC	European Commission
ESA CCI	European Space Agency Climate Change Initiative
EU	European Union
EU	European Union
FGD	Focus Group Discussion
GGE	Google Earth Engine
GHG	Greenhouse Gas Emissions
GIS	Geographic Information Systems
GLAD	Global Land Analysis and Discovery
IIASA	International Institute for Applied Systems Analysis
IPBES	Intergovernmental Panel on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
LC	Land Cover
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment

LUC	Land use change
LULUC	Land use land use change
MoA	Ministry of Agriculture Argentina
OI	Occupation Impact
PDF	Potentially Disappeared Fraction of Species
PY	Paraguay
RSPO	Roundtable on Sustainable Palm Oil
RTRS	Roundtable for Responsible Soy
SC	Supply Chain
SDG	Sustainable Development Goal
SEI PCS	Spatially Explicit Information on Production to Consumption Systems
SI	Supplementary Information
SOC	Soil organic carbon
SSP	Shared Socioeconomic pathways
TI	Transformation Impact
TNC	The Nature Conservancy
UK	United Kingdom
UN FAO	United Nations Food and Agriculture Organization
UN	United Nations
UNEP	United Nations Environment Programme
USA	United States of America

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