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Addressing Land Use Change Leakage in Sustainable Land Use Financing and 'Deforestation-Free' Claims

By Michele De Rosa and Jannick Schmidt. One Planet Foundation. Amersfoort, January 2020

“Remember that all models are wrong;

the practical question is how wrong do they have to be to not be useful."

G.E.P. Box & N.R. Draper,

in Empirical Model-Building and Response Surfaces (1987)

Preface

One Planet Foundation developed this publication in 2020, as a contribution to the UNEP project titled "Addressing Land Use Changes Leakage in Sustainable Land Use Financing and 'Deforestation Free' Claims" of the UNEP Life Cycle Initiative. The views expressed in this publication are those of the authors and do not necessarily reflect the views of the United Nations Environment Programme. We regret any errors or omissions that may have been unwittingly made.

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List of abbreviations

ADP	Amsterdam Declaration Partnership
AEZ	Agro-Ecological Zone
AFOLU	Agriculture, Forestry and Other Land Uses
CDM	Causal Descriptive Model
CAFI	Central African Forest Initiative
CARD	Centre for Agricultural and Rural Development
CNFAP	Centre for National Food and Agricultural Policy
CIRAD	Centre de coopération Internationale en Recherché Agronomique pour le Développement
CGE	Computable General Equilibrium
dLUC	direct Land-Use Change
EEM	Economic Equilibrium Model
EPIC	Environmental Policy Integrated Climate
FAPRI	Food and Agriculture Research Institute
GCF	Green Climate Fund
GIS	Geographic Information System
GLOBIOM	Global Biosphere Management Model
GTAP	Global Trade Analysis Project
GWP	Global Warming Potential
HCV	High Conservation Value
HMRIO	Hybrid Multi-Regional Input-Output
IAM	Integrated Assessment Model
IFPRI	International Food Policy Research Institute
IIASA	International Institute for Applied Systems Analysis
iLUC	indirect Land-Use Change
IMPACT	International Model for Policy Analysis of Agricultural Commodities and Trade
INRA	Institut national de la recherché agronomique
IPCC	Intergovernmental Panel on Climate Change
LCA	Life Cycle Assessment
LCI	Life Cycle Initiative
LUC	Land-Use Change
LPJmL	Lund–Potsdam–Jena dynamic global vegetation model with managed lands
MAgPIE	Model of Agricultural Production and its Impact on the Environment
NM	Normative Model
PE	Partial Equilibrium
PW	Productivity weight
REDD+	Reducing Emissions from Deforestation and Forest Degradation plus forest conservation, sustainable management of forests and enhancement of forest carbon stocks
REMIND	Regional Model of Investments and Development
RLU	Royal Lestari Utama
USDA	United States Department of Agriculture
UNEP	United Nation Environmental Programme
UNFCCC	United Nations Framework Convention on Climate Change
WBCSD	World Business Council for Sustainable Development
WRR	Word Resources Institute

1 Introduction

Land is an essential resource for the production of food, feed and bio-based material and supports ecosystem services that guarantee the ecological equilibrium and the human existence. While pro-capita consumptions and population trends tend to increase, land remain a finite natural resource. It is, therefore, not easy to reconcile development, biodiversity conservation and climate change mitigation efforts. According to the IPCC, in 2010 Land Use Change (LUC) and Agriculture, Forestry and Other Land Uses (AFOLU) cause 24% (12 Gt CO_2 eq.) of the global (net) GHG emissions (IPCC 2014, AR5 p 46): 10-12% from agricultural production and 9-11% from land use and land-use change activities (IPCC 2014, AR5 p 869). The AFOLU emissions may further increase by up to 30% in 2050 if the *status quo* remains unchanged (FAO 2014).

The need to identifying a sound methodology to secure "deforestation-free" products has been expressed by several institutions. In Europe, seven countries showed high interest in the related concept of "deforestation-free" commodities. This interest led to the Amsterdam Declaration on (2015). Denmark, France, Germany, Italy, Norway, The Netherlands and the Unite Kingdom signed the Amsterdam Declaration on deforestation and the Amsterdam Declaration on Sustainable Palm Oil, launched in 2015 in the context of the Paris Climate Agreement. The goal of the Amsterdam Declaration Partnership (ADP) is to guarantee "deforestation-free" sustainable commodities, recognizing the importance of tropical forests and their conservation through responsible supply chain management (Amsterdam declaration 2015).

The United Nations Environmental Programme (UNEP) is working to identify areas that can be allocated for development and areas that should be off-limits in order to conserve forests and biodiversity, ensuring that stakeholders are consulted and minimum standards for land use planning processes are respected (UNEP 2018).

Towards a zero-deforestation commitment, UNEP is seeking to avoid or reduce the occupation of further land resources, especially in High Conservation Value (HCV) areas, rich in biodiversity and carbon (UNEP 2018). To achieve this goal, UNEP's Life Cycle Initiative (LCI), which aims at addressing the environmental impact of production and consumption from a product's life-cycle prospective, launched a project titled "Addressing Land Use Change Leakage in Sustainable Land Use Financing and 'Deforestation Free' Claims". The Life Cycle Initiative has engaged with colleagues in the UNEP Sustainable Land Use Financing Unit in discussions on how to support the Environmental and Social Impact Framework to grant investments. A key issue is how to guarantee that products do not cause deforestation in their supply chain, i.e. directly by transforming forested land but also indirectly, by forcing other producers to transform forested land somewhere else.

Several methodologies exist to quantify the impacts of LUC: some attempt to trace large-scale LUC resulting from national or transnational land use policies, other focus on the LUC occurring as a consequence of production activities and how changes on product systems or management practices may reduce LUC impacts. The UNEP LCI intends to identify LUC models that could provide useful insight on LUC impact caused by production activities or avoided by changes in production practices, in order to support claims of deforestation-free commodities. Depending on the scope and ambition, LUC models vary widely in complexity, computational intensity and applicability. Attempts to quantify the LUC impact using Life Cycle Assessment (LCA) have often applied a mix of causal-descriptive models based on biophysical relationships on the one hand and economic models on the other, the latter describing the international trade of products and thus the market mechanisms involved. The complexity of the topic has also led to the rise of a mores simplistic approach, based on normative assumptions, to calculate LUC emissions with a GHG factor multiplied over an arbitrary period (De Rosa et al. 2016), e.g. 20 years. A transparent, verifiable and sound methodological approach for the quantification of LUC-related impacts worldwide is necessary to provide policy-makers with the information required for setting in place policy mechanism directing investments. It is particularly important that action aiming at reducing deforestation avoids leakage, i.e., ensuring that the loss of forests is avoided instead of being shifted somewhere else.

1.1 Direct and indirect Land-Use Change

Environmental assessments have long underestimated the consequences of using land as a production resource (Schmidt et al. 2015; De Rosa et al. 2016). When land-use effects are accounted for, this often refers to the consequences of modifying a specific area from one land use to another, i.e., a *direct* Land-Use Change (dLUC). A major discourse shift occurred after the publication of the works of Fargione et al. (2008) and Searchinger et al. (2008), discussing indirect Land-Use Change (iLUC), i.e., a change in land use caused indirectly as an upstream consequence of a land use taking place somewhere else in the world (De Rosa et al. 2016). The iLUC effect is often also referred to as the land leakage effect or knock-on effect, reflecting the fact that land use may "leak", i.e., trigger unintended indirect (knock-on) changes somewhere else. In this report, we use the definition of iLUC and dLUC as of Schmidt et al. (2015) "*… dLUC are defined as those changes that occur on the same land as the land use, while iLUC are defined as the upstream life cycle consequences of the land use, regardless of the purpose of the land use. Examples of dLUC include changes in soil carbon content due to a certain cultivation practice, while examples of iLUC can be deforestation and cropland intensification that take place somewhere else than the land use.*" Land-Use leakages are caused by an increasing demand of land for the production of bio-based products. However, they may also occur as a consequence of increasing land demand for nature conservation purposes. In other words, the implementation of nature conservation in a geographical area does not necessarily guarantee that the displaced land production capacity will not be provided by another forested area somewhere else. Therefore, by definition, iLUC always occur, unless the land occupied is outside the general market for productive land, e.g. if it is degraded abandoned agricultural land. In this case, no production is displaced and no iLUC is triggered.

Quantifying the environmental iLUC impacts is challenging because it requires tracing the cause-effect relationship between the demand for products that require input of land as a production resource (e.g., bio-based products) and the actual location of the LUC triggered by such demand. This requires the identification of the marginal source of land on a global scale. Countries rely heavily on international trade of commodities and products are often supplied from very distant countries. A globalised supply-chain contributes to the complexity of tracing the interlinked environmental impact of these commodities.

1.2 Objectives

The objective of this study is to support the work of the Land Use Financing Unit and the Life Cycle Initiative of the UNEP by identifying suitable LUC models to quantify the LUC impacts of commodity productions. These models shall be able to provide recommendations on how land-use policies may reduce deforestation embedded in commodity supply-chains. "Deforestation-free" commodities imply that no deforestation is embedded, neither direct nor indirect, in the products' supply-chain. Claims of "deforestation free" commodities therefore requires the quantification of iLUC at the commodity level. To achieve the objective, the report answers the following questions:

1. What type of LUC model is more suitable and applicable to support claims of "deforestation free" supply chain or commodities?
2. Which criteria should be applied by investors concerned with achieving a net deforestation reduction through protection of natural land (e.g. forest protection in land use concessions) and avoidance of indirect Land-Use Change?

In order to address the research questions, the report is structured as follows: Section 1.3 introduces some of the challenges in quantifying the benefits of forest conservation activities. Section 2 provides an overview and comparison of existing models. Section 3 discusses cases of LUC in tropical regions. It also shows how some of the tools introduced in section 2 may support claims of zero deforestation or quantify the reduction of LUC-related environmental impacts. Section 4 provides recommendations on key aspects to consider in land use planning and land use financing.

1.3 Challenges in quantifying the benefits of forest conservation activities

Despite efforts to reduce the loss of forest land worldwide, deforestation has continued to occur over the last fifty years, even though the land occupied by permanent meadow and pasture began decreasing in the 90´s (**Figure 1.1**). Almost all deforestation in recent times took place in tropical forests (FAO 2012); the richest forest in terms of carbon and biodiversity content and also the most productive land not already converted to agriculture.

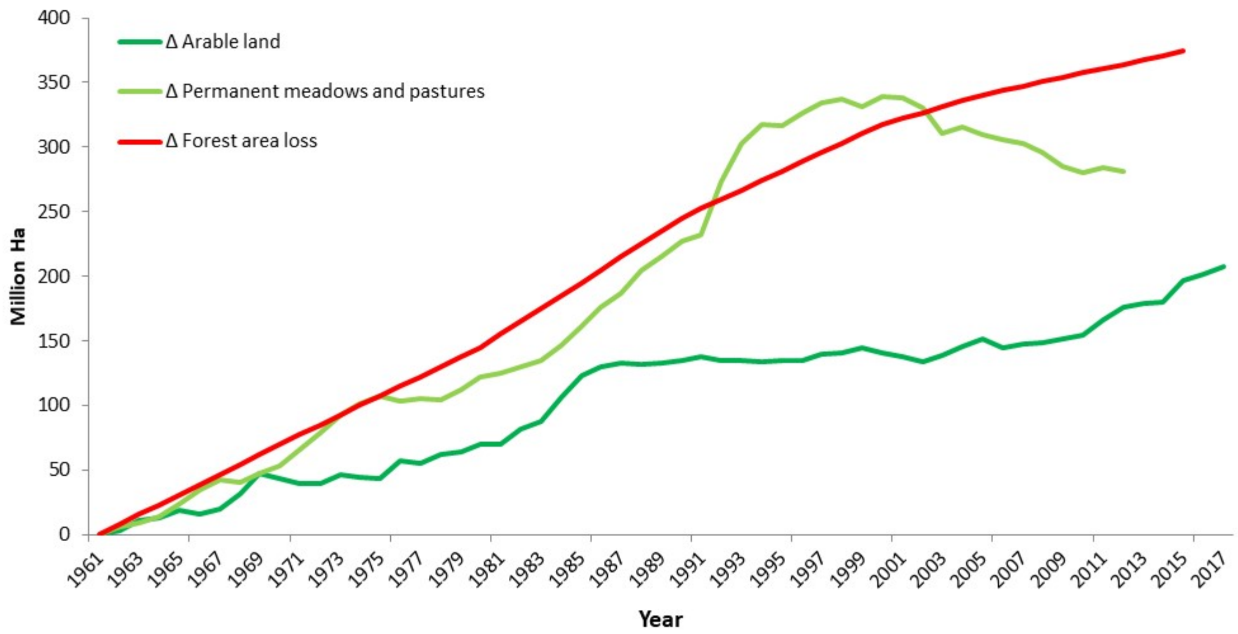


Figure 1.1 Cumulative global forest area loss, arable land and permanent meadows and pastures since 1961. The arable land area includes the area cultivated with permanent crops. All data are from the FAOSTAT database (2019). FAOSTAT forest data are only available from 1991. Data on forest cover before 1991 are estimated based on the deforestation trends reported by the FAO's 'State of the World's Forests' report (FAO 2012 Figure 1, page 9).

While there are many efforts aiming at reducing or halting deforestation in tropical regions, there are also many drivers to convert tropical land to agriculture that may neutralize these efforts. Many large tropical countries are emerging economies, supplying a large share of global agricultural commodities, vital to supply food to the growing global population (see section 3.3). Initiatives to reduce forest losses must guarantee that the avoided land conversion will not simply result in burden-shifting, moving the threat of deforestation to other areas (within or outside a nation's own borders). Such a knock-on effect may in fact result in the loss of forested area with an even higher value in terms of carbon stock and biodiversity.

Current mechanisms to halt deforestation aim either at ensuring deforestation-free supply chains (commodity based), such as the ADP (Amsterdam declaration 2015), or providing financial compensation for avoiding conversion of tropical forest (land policy based), such as the REDD+[1] of the United Nations Framework Convention on Climate Change (UNFCCC). For both types of initiatives, there is a lack of focus on the potential iLUC effect. The Amsterdam Declaration was signed only four years ago, at the end of 2015, making it premature to evaluate the impact that the ADP could be currently having. REDD+ is a development mechanism aiming at offsetting carbon dioxide with investment in tropical forest conservation. The REDD+ schema awards payment to countries proving reduced emissions from deforestation compared to a forest reference emission level (expressed in tonnes CO_2/year). Reference levels serve as benchmarks for assessing each country's performance in implementing REDD+ activities (REDD+ 2019). They are periodically updated to reflect new trends, new knowledge, and changes in methodologies or scope. Countries implement national forest monitoring systems to assess whether GHG emissions related to forest land decreased over a period and to claim result-based payment when this is the case. However, a country-based evaluation does not guarantee that no spill-over effects occur beyond the country borders. The REDD+ schema does not include any assessment of the potential iLUC effects of the conservation activities when measuring country performances.

Overall, two aspects are crucial to verify the benefits of initiatives to halt deforestation:

1) That iLUC effects do not offset the benefit of the action, or at least not completely. This requires that the iLUC effect is estimated using a sound and robust methodology;
2) That the benefit of the action would have not been achieved if the action did not take place (i.e., the *additionality* of the benefit). This requires proving that the achieved environmental gains are additional compared to a baseline scenario without the initiative.

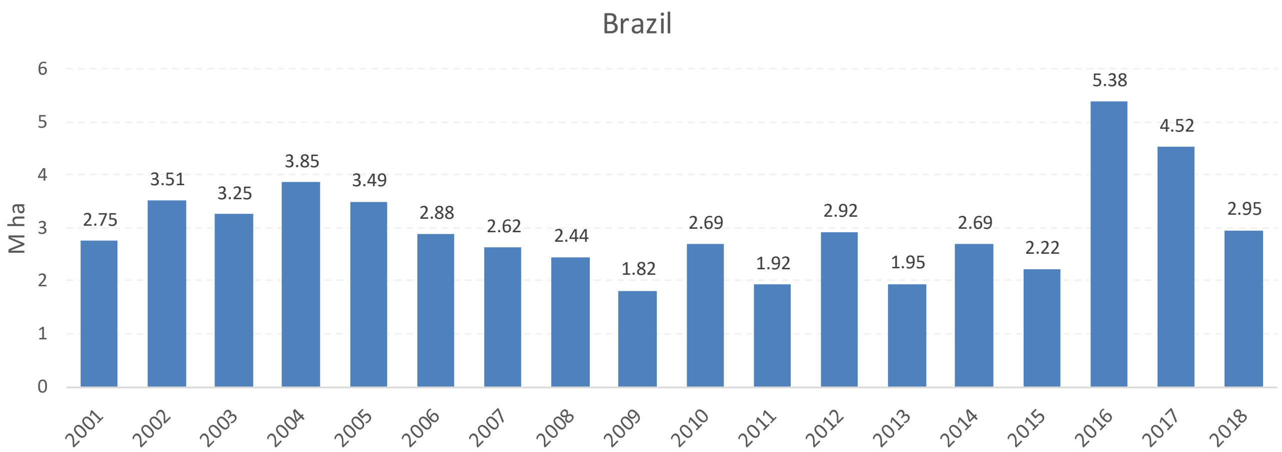
The iLUC impact of this type of initiatives is difficult to quantify at national level without a specific analysis of the affected commodity or land policy, for two reasons: First, the indirect effects propagate in the often very complex supply-chains of the commodities that involve many stakeholders both on the supply and the demand side (see section 3.1). Second, the magnitude of the area affected by these initiatives is usually small (see calculations in Appendix 2) compared to the forested area affected by LUC (**Table 1.1**).

Table 1.1. Countries with largest share of primary tropical forest and respective tropical forest loss, i.e. forests in countries between the Tropic of Cancer and the Tropic of Capricorn. Data from Global Forest Watch (2019). The data use a 30% canopy cover definition for forest.

Country	Primary forest in 2018 (M ha)	% of global primary forest	Loss of primary forest 2001 - 18 (M ha)	% Loss (2001 - 18)
Brazil	320	34.8%	23.2	6.7%
D.R. Congo	100	10.9%	4.4	4.2%
Indonesia	85	9.2%	9.2	9.8%
Peru	67	7.3%	1.8	2.6%
Colombia	53	5.8%	1.4	2.5%
Bolivia	38	4.2%	2.5	6.0%
Venezuela	38	4.1%	0.4	1.1%
Papua New Guinea	32	3.5%	0.7	2.1%
Gabon	22	2.4%	0.2	1.0%
Republic of Congo	21	2.3%	0.3	1.4%
Others	143	15.6%	6.6	4.4%
Total	**921**	**100%**	**51**	**5.5%**

[1] Reducing Emissions from Deforestation and Forest Degradation plus forest conservation, sustainable management of forests and enhancement of forest carbon stocks

The participation in actions to reduce deforestation may reflect a political willingness to preserve natural habitat. Therefore, the engagement in REDD+ could be a proxy measure of a country's political engagement in reducing deforestation, for example in Brazil and in the Democratic Republic of the Congo (D. R. Congo), the two countries with the largest area of primary tropical forest in the world albeit with significantly different engagement in the REDD+ schema. D.R. Congo, has considerably less involvement in the REDD+ schema compared to Brazil[2]. **Figure 1.2** shows that the total loss of tree cover in Brazil reduced from 2004 until 2010. However, this trend reverted 2016. Commodity-driven deforestation is the main cause of deforestation in Brazil, i.e. permanent conversion of forest and shrubland to a non-forest land use, such as agriculture, mining, or energy infrastructure (Curtis et al. 2019; observed on Global Forest Watch 2019). The reduced deforestation rate in Brazil has been achieved almost entirely by reduction of commodity-driven deforestation.



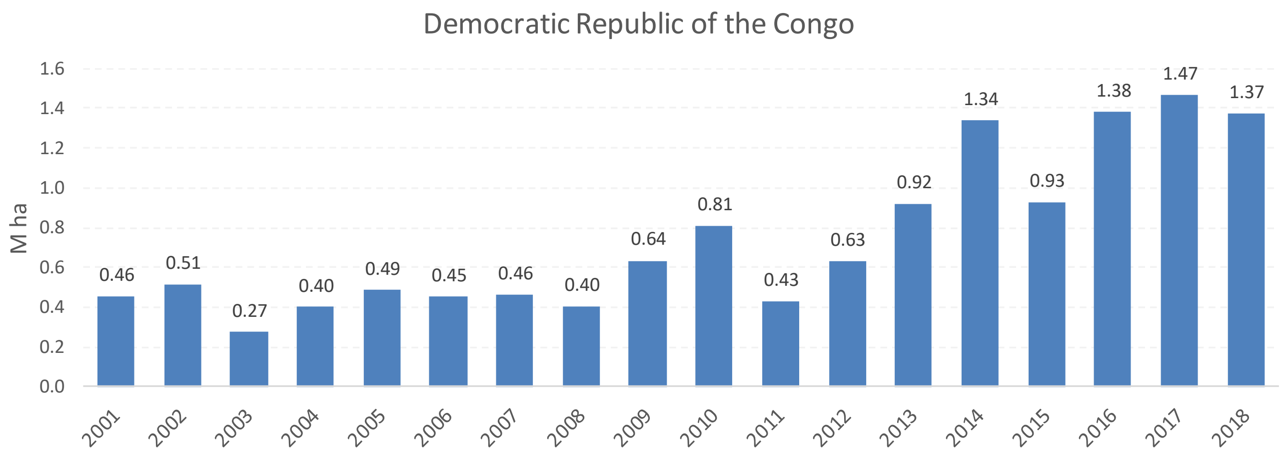


Figure 1.2 Hectares of tree cover loss at a national level, between 2001-2018.Data from Global Forest Watch (2019). The data use a 30% canopy cover definition for forest. These estimates do not consider tree cover gain and account for total tree cover.

On the contrary, in D.R. Congo, the deforestation rate has been almost constantly increasing (Global Forest Watch 2019). The main driver of deforestation in D.R. Congo has instead been almost entirely shifting agriculture, i.e. small to medium-scale forest and scrubland conversion for agriculture that is later abandoned and followed by subsequent forest regrowth (Curtis et al. 2019, observed on Global Forest Watch 2019).

[2] The REDD+ schema has not yet granted payments to D.R. Congo. As many countries in the Congo basin, D.R. Congo developed a 'REDD-Readiness Preparation Plan' which includes the annual submission of forest reference levels. Yet, currently, no-carbon credit payment has been granted to D.R Congo (REDD+ 2019): in 2018 the Central African Forest Initiative (CAFI) froze payment to D.R. Congo after the country's ministry of environment awarded illegal logging concessions, in breach of an existing moratorium (CAFI 2018).

However, when looking at tree forest cover trends in tropical areas globally (**Figure 1.3**), tropical deforestation trend does not seem to be significantly affected by the deforestation reduction registered in Brazil and that the overall trend appears constant or increasing in the latest three years (Global Forest Watch 2019). This suggest that the increasing global demand for land led to a shift in the marginal supplier of land to countries with lower institutional commitment in reducing deforestation but it has not reduced the deforestation trend at a global level.

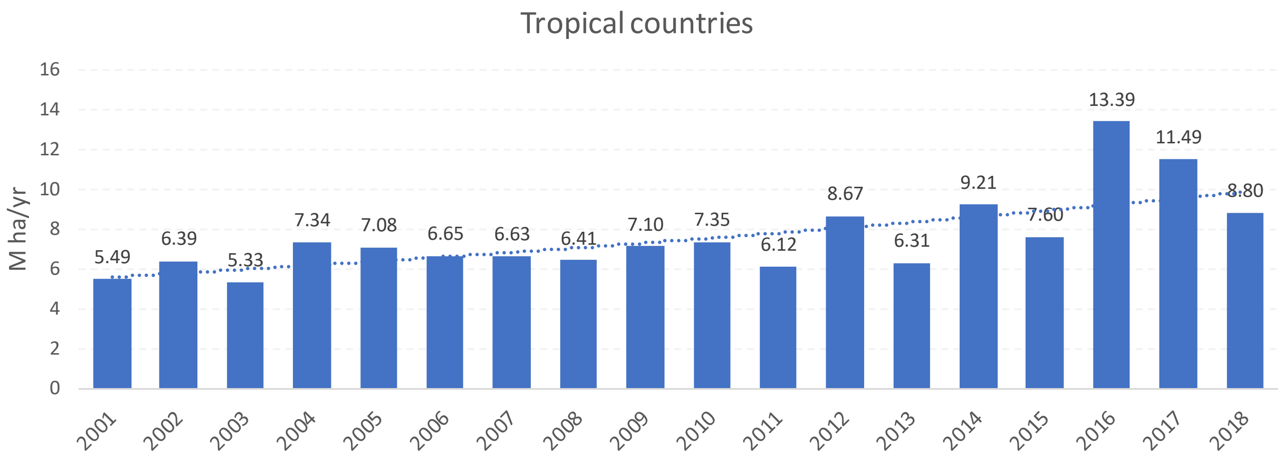


Figure 1.3 Total hectares of tree cover loss between 2001-2018 in tropical countries, i.e. countries between the Tropic of Cancer and the Tropic of Capricorn. Data from Global Forest Watch (2019). The data use a 30% canopy cover definition for forest. The estimates do not consider tree cover gain.

Although political willingness and investment to halt deforestation may slow down the deforestation rate in some countries, they may also trigger an increasing deforestation somewhere else (i.e., the leakage effect), because of the continuously increasing demand for land at the global scale. Furthermore, a major concern of conservation schemes is to ensure the long-term persistence of the biodiversity and carbon stored in conservation areas. In this perspective, the increased deforestation trends the 2016 (**Figure 1.3**) and the 2019, with a dramatic increase in forest loss due to forest fires in Brazil, launched an alarming signal. According to the Brazilian's National Space Research Institute (INPE), in 2019 the deforestation in the Brazilian Amazon rose by 30% compared to 2018 (INPE 2019). This alarming deforestation rate raises the concern that a tipping point may be reached beyond which the Amazon ecosystem may convert to a non-forest ecosystem (Lovejoy and Nobre 2018).

1.4 The land sector can reduce global GHGs

In October 2019, a Nature Climate Change's article (Roe et al. 2019) showed a roadmap of priority measures and regions to achieve the 1.5°C temperature goal set by the Paris Agreement. The authors show the great potential contribution of the land sector to limit global warming to 1.5°C above pre-industrial levels. Among those, the forest-based actions could provide more than half of the GHG emissions reductions required to achieve the goal (Roe et al. 2019). In particular, the two largest reduction could be achieved by reducing GHG emissions from deforestation and by restoring forests, wetlands and drained peatlands.

In order to prioritize land uses to achieve these objectives, it is essential to quantify the dLUC and iLUC. Indirect land uses are embedded in any commodity supply-chain. Nearly all countries in the world export and import bio-based products requiring land's production capacity. **Figure 1.4** shows the regions that are net exporters (in green) and net importers (in red) of this production capacity: some regions provide the global market with more land than the land embedded in their own consumptions (for example Africa, Latin America and North America and Oceania). Other regions embed in their own consumptions more land than the land they provide to the global market (e.g. China, Russia, The Middle East and Europe).

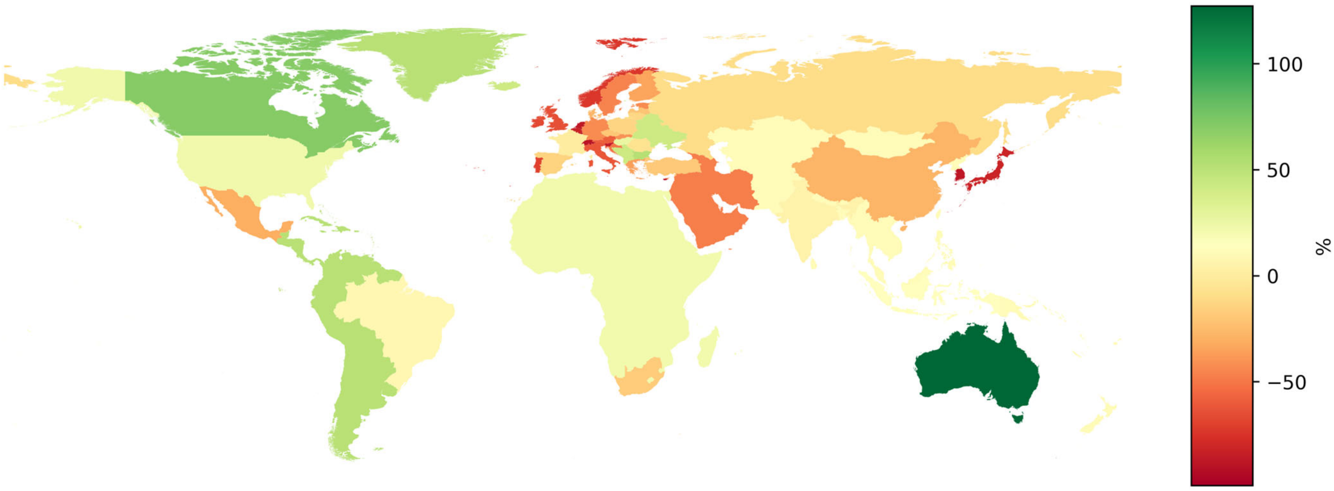


Figure 1.4 Global land use balances shown for countries and regions defined in the Input-Output database EXIOBASE (Stadler et al. 2018; Merciai and Schmidt 2017). Red indicates a region that is a net importer of land's production capacity. Green indicates a region that is a net exporter of land's production capacity. The figure is based on an own elaboration of LUC data which allowed to obtain the region's own land used for commodity production and the total land embedded in the region's own consumption. The difference between the two provides the land balance. The land balance is then normalized by dividing it for the region's own land used for commodity production.

Modelling global LUC requires a holistic understanding of the global trade of bio-based products and the demand for land worldwide. This is necessary to verify that land use leakage is not occurring as an unintended, indirect consequence of changes in resources uses or that a land use decision generates a net environmental benefit. Avoiding land leakage is therefore a complex matter and it requires accounting for trade-offs between increasing demands of land for food, biomaterials, biofuels and for ecosystem services. A number of models, following different approaches, exist to perform such analyses. These are based on different methodologies and vary largely depending on their scope and the objective they intend to achieve. The following chapter provides a broad overview of some of the most renowned modelling approaches applied to perform global analysis of land resources and to calculate the associated environmental impacts.

2 Approaches to quantify Land-Use Change

Approaches to model LUC vary mainly in their goal and scope. This chapter attempt to categorise the models based on their main characteristics. For each category, relevant models are introduced and their main advantages and disadvantages are listed. The models are then compared based on criteria for their applicability, transparency and key methodological aspects. The purpose is to identify the most suitable modelling approach to quantify the direct and indirect LUC associated to the production of commodities and thus supporting land uses that would achieve a net environmental benefit. The LUC model should be applicable to support the UNEP Life Cycle Initiative and the Sustainable Land Use Financing Unit in setting up land use financing mechanism aiming at reducing deforestation.

Modelling the link between production of goods and land use requires an interdisciplinary modelling approach, often relying on multiple data sources such as trade data, geo-spatial information and agricultural data. Because LUC models typically rely on hybrid methodologies, it is difficult to make sharp distinctions between different LUC modelling frameworks. Nevertheless, three main methodological approaches can be identified for assessing the LUC effects related to land use (De Rosa et al. 2016):

- Economic Equilibrium models (EEM): primarily, though not exclusively, relying on trade and economic data to trace land uses worldwide;
- Causal-descriptive models (CDM): primarily, though not exclusively, relying on biophysical links to describe causal relationships;
- Normative models (NM): mostly relying on rule-based assumptions, where normative principles are applied for the calculation of LUC and to distribute the environmental effects to commodities.

Table 2.1. A list of the most common models applied for assessing LUC associated with bio-based production. CDM: Causal-Descriptive model; CGE: Computable General Equilibrium model: IAM: Integrated Assessment Model; NM: Normative Models; PE: Partial Equilibrium model.

Model name	Model type	Description
Economic Equilibrium models (EEM)		
CAPRI	PE	Common Agricultural Policy Regionalized Impact Modelling System (European Commission)
FAPRI-MU	PE	Food and Agriculture Research Institute (University of Missouri-Columbia)
FARM	CGE	Future Agricultural Resources Model (USDA)
FASOM	PE	Forestry and Agricultural Sector Optimization Model (USDA)
GLOBIOM	PE	Global Biosphere Management Model (IIASA)
GTAP-AEZ	CGE	Global Trade Analysis Project – Agro Ecological Zones
IMPACT	PE	International Model for Policy Analysis of Agricultural Commodities and Trade (IFPRI)
LEITAP	CGE	Landbouw Economisch Instituut Trade Analysis Project
MAGNET	CGE	Modular Applied GeNeral Equilibrium Tool (LEI Wageningen UR)
MAgPIE	PE	Model of Agricultural Production and its Impact on the Environment
Causal Descriptive models (CDM)		
2.-0 LCA iLUC	CDM	Causal Descriptive Model of global iLUC for Life Cycle Assessment.
Bauen et al (2010)	CDM	Causal Descriptive Approach to Modelling the GHG Emissions Associated with the Indirect Land Use Impacts of Biofuels. UK Department for Transport.
GlobAgri-WRR	CDM	A version of the Biophysical GlobAgri model developed by CIRAD, INRA, WRI, and Princeton University.
IMAGE	CDM/IAM	Integrated Model to Assess the Global Environment (PBL Netherlands Environmental Assessment Agency)
Normative models (NM)		
GHG emission protocol	NM	A Corporate Accounting and Reporting Standard (World Resources Institute)
PAS 2050	NM	Publicly Available Specification
Quantis LUC	NM	Guidance for measuring GHG emissions from land, forests, and soils across the supply chain

Table 2.1 lists some of the most common models used to estimate the environmental impact associated with LUC. The table classifies the models according to the three main approaches described above. The main characteristics of the models are described below.

2.1 Economic Equilibrium models

Based on the economic equilibrium theory, Economic Equilibrium Models (EEMs) assume that shifts in supply and demand cause price fluctuations, which lead to price adjustments across markets and ultimately a new market equilibrium. In other words, the principle is that endogenous adjustments in market prices lead to the equality between supply and demand for each product and in each region included in the model. Prices are influenced by resource availability, policies regulating access, and technological change. When a production activity requires land resources, the equilibrium moves towards another point with a new configuration of demand, supply and prices that generate a new equilibrium with a new level of environmental impacts. The land occupation and the related emissions are among the impacts that can be estimated.

Economic models can be further divided in partial equilibrium (PE) models or computable general equilibrium (CGE) models depending on whether they describe the entire world economy or a specific sector and/or region. Partial Equilibrium models (PEs) models focus on subsets of the total economy, including few economic sectors to represent them with a fine level of detail. In PE models the economic equilibrium must only be reached within the economic sectors included in the model. With respect to agricultural and land use analysis, the peculiar advantage of a PE models is the capacity to capture price dynamics in the land-using sectors with substantial spatial and land management detail. However, PEs do not include effects on the rest of the economy and therefore also not feedback effects from the the restof the economy on the sectors represented in the model. Computable General Equilibrium models (CGE) do not have this limitation: they represent the entire global economy, including inter-sectoral influences. However, this is typically at the expense of sector detail. Table 2.1 shows some of the most relevant models that have been used to assess the LUC of agricultural commodities and their environmental impacts.

Different modelling approaches are often combined to overcome their respective limitations. For example, PE models can integrate outputs from CGE models to include relevant feedback effects caused by an economic sector not included in the partial equilibrium model. In these cases, the model is often described as an Integrated Assessment Model (IAM), which can include a broad variety of model types. The last two models described in this section, GLOBIUM and MAgPIE, are EEM that are commonly coupled with other models and operated as Integrated Assessment Models. IMAGE, described below, is an example of a model developed as an Integrated Assessment Model (IMAGE).

The first models

One of the first PE models was FAPRI (Food and Agriculture Research Institute) established in 1984 as a dual university programme with research centres at the Centre for Agricultural and Rural Development (CARD) at Iowa State University and the Centre for National Food and Agricultural Policy (CNFAP) at the University of Missouri-Columbia. Currently CARD is not actively using FAPRI and research occurs at the University of Missouri (FAPRI-MU 2019). The model provides market and policy analysis for the agricultural sector in the USA. The Future Agricultural Resources Model (FARM), developed by the US Department of Agriculture (USDA), as an aggregation and extension of an early version of the Global Trade Analysis Project (Darwin et al. 1995, p 45), and was the first CGE model integrating a geographic information system (GIS) with spatially explicit bioclimatic data to disaggregate land categories based on the length of the growing period.

GTAP-AEZ

An extensive and widely used CGE is the results of the Global Trade Analysis Project (GTAP), a network of scientists led by Purdue University, USA. GTAP is a global model, covering all regions and major countries in the world. GTAP- AEZ (Agro-Ecological Zones) is a version of GTAP for detailed economic modelling of land use. GTAP- AEZ introduces land competition within a given agro-ecological zone and it features an extensive land-use database to account for the opportunity costs of alternative land uses or land-based mitigation strategies. It includes 18 agro-ecological Zones, 6 growing periods and 3 climatic zones (temperate, tropical and boreal), each divided in 6 categories, thus allowing a more detailed representation of land-based emissions and forest carbon sequestration (GTAP, 2008). The agro-ecological zones are used to constrain the competition for land within a given zone to the activities that have been observed to take place. Based on the principle of rent maximization, the CGE implements a nested Constant Elasticity of Transformation (CET) of land supply that describes how land changes between alternative uses. The model assumes that, in order to maximize the land rent, land owners allocate land between three different economic uses: forest, cropland and grazing land, based on alternative returns to land. Within each specific use type, the land owner further allocates the land between various crops, again based on the relative return. GTAP-AEZ also incorporates a forest carbon stock database, including detailed regional forest inventory and forest carbon stock data.

Several models stem from the standard GTAP model. LEITAP is a global CGE model initiated in 1996 based on the standard GTAP model and it was especially extended to the agricultural sector to account for the use of agricultural products like wheat, maize, and sugar, as intermediate inputs (Woltjer et al. 2007). This allowed assessing land use and biofuel policies by accounting for impacts on land use, environment, and other food-related products. LEITAP implemented land-supply curves taking into account land heterogeneity and limited availability of land (Eickhout et al. 2008). LEITAP's successor, MAGNET (Modular Applied GeNeral Equilibrium Tool) is a multi-regional, static CGE modelled facilitating the addition of extensions around the GTAP model core (Woltjer et al. 2011, Woltjer and Kuiper 2014). First LEITAP and later MAGENT have been integrated in "The Integrated Model to Assess the Global Environment" IMAGE model. IMAGE version 3.0 (IMAGE v3.0) is a comprehensive integrated assessment modelling framework, which means it links multiple models to draw on functional relationships between human activities and their impact, for example the provision of food, water, energy and their impacts. Integrated assessment models are not EEMs although they may make use of them. For this reason, IMAGE is further discussed in the section 2.2, dealing with causal-descriptive models.

Table 2.2. Highlights of the GTAP model: pros and cons.

Pros	Cons
The model has detailed land-use categories based on agro-ecological zones	The model is complex to run and it requires expert knowledge
A dedicated version of the economic model is specifically designed for land-use policy analyses	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
It has global geographical coverage	It does not avoid amortization to allocate LUC emissions over time

CAPRI

The 'Common Agricultural Policy Regionalized Impact Modelling System' (CAPRI, 2014) is a European PE model developed with European Commission research funds. The model is open source and it is maintained by a Pan-European network of researchers. Integrated analysis of the EU agricultural policies also combined CAPRI and the general equilibrium model GTAP (Britz and Hertel, 2011; Pelikan et al., 2015). CAPRI models the global agricultural sector, with a specific focus on the European region (EU27, Turkey and Western Balkans).

The tool package comprises a database, an economic model and software tools (CAPRI 2014). The economic model links a supply module, a market module, and a regional CGE (Figure 2.1). The supply module consists of models representing the activities of farmers at regional or farm type level, including about 50 crop and animal activities for each of the around 280 regions or about 2500 farm type models for EU27 (CAPRI 204). The supply module of CAPRI features a land supply curve, for each region and farm type, based on the marginal return to agricultural land. CAPRI also models the substitution between permanent grass land and arable land (CAPRI 2014). The CAPRI global market model is a comparative static Multi-Commodity model with bi-lateral trade flows based on FAOSTAT (Figure 2.1), covering 47 primary and secondary agricultural products (CAPRI 2014).

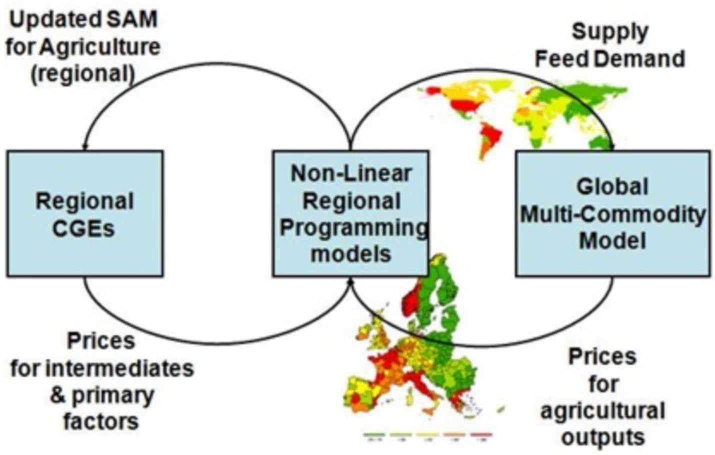


Figure 2.1 Overview of the CAPRI model. Source: CAPRI webpage www capri-model.org. The figure is a simplified illustration of the model. It shows the three main model components: the supply module, consisting of independent, aggregate non-linear programming modules; the Market module (Global Multi-Commodity Model), and the regional CGEs, including an independent model for each European country. This report does not describe in detail all the elements of the model presented in this figure. For a detailed description of the model, see CAPRI (2014).

CAPRI embeds a regional independent CGE model for each European country, covering all economic activities disaggregated in 11 sectors. CAPRI includes 21 land-use classes (CAPRI 2014, p 274), including both productive and not, and 16 aggregated classes. Although the model is linked to biophysical models, for land use policy analyses, the existing applications do not account for the iLUC effects. Renwick at al. (2013) coupled CAPRI with a spatially explicit land allocation model, the Conversion of Land Use and its Effects (Dyna-CLUE) model, to assess EU agricultural policy reforms. The authors recognize that the changes in EU agriculture also have impacts outside EU through changes in trade of agricultural commodities. Nevertheless, the methods they applied allows only an analysis limited to the LUC within EU (Renwick et al. 2013 p. 453). Similarly, Britz and Delzeit (2013) used CAPRI for analysing the impact of German biogas production in terms of land use and environmental consequences. They recognize that iLUC occur when more crops are demanded in the EU because the displaced agricultural output must be produced elsewhere. Yet, while the authors account for the increasing inputs necessary for land intensification, they do not account for the effect of land expansion because their analysis lacks a global land use model (Britz and Delzeit 2013 p. 1274).

Table 2.3. Highlights of the CAPRI model: pros and cons.

Pros	Cons
The model is open source	The model requires CAPRI's expert knowledge
It is specifically designed for land use analysis	It is designed with focus on the EU
It is linked to a bio-physical model	It does not account for iLUC consequences of land expansion
	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
	It does not avoid amortization to allocate LUC emissions over time

IMPACT

The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) is a PE model, first developed by the International Food Policy Research Institute (IFPRI) in 1990 to provide support for long-term policies addressing food provision, natural resource protection, and development. The latest version of IMPACT (version 3) dates 2015 (IMPACT 2015). The model has been applied to support decision making by the Word Bank, the Asian Development Bank, FAO and national governments, as well as to a number of studies on regional issues, commodity-level analyses, and crosscutting thematic issues. IMPACT models supply, demand and prices of 62 agricultural commodities in 159 countries and it includes food production functions for 320 geopolitical regions (IMPACT 2015). This model does not have specific focus on land use types: crop production is determined by area and yield response functions for irrigated and rainfed cultivation. The harvested area is determined based on the price of the analysed crop and of the competing crop prices, as well as projected exogenous trends in the harvested area. These are trends resulting from factors independent from crop prices, such as increasing population or soil degradation.

IMPACT also includes a climate model which provides climate data such as temperature and precipitation as an input to the crop simulation model. IMPACT has a special focus on modelling the impact of water availability in relation with climate change and crop yields. IMPACT-WATER is an extended version of IMPACT, forming an integrated assessment model with focus on water resources. The model is obtained by combining IMPACT with a global hydrology model, balancing water availability and water uses in different economic sectors at regional and global scale.

Table 2.4. Highlights of the IMPACT model: pros and cons.

Pros	Cons
The model has a global geographical cover	The model it is not publicly available
It accounts for both land intensification and land expansion	Running simulations requires insider expert knowledge
	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
	It does not avoid amortization to allocate LUC emissions over time

FASOM

The Forestry and Agricultural Sector Optimization Model (FASOM GHG) is a dynamic, linear programming PE model developed by the USA Environmental Protection Agency (Adams et al. 1996). FASOM was initially developed to evaluate the market and welfare implications of sequestering carbon in trees. Currently, FASOM GHG is used to assess the dynamic effects of policies affecting the forestry and agricultural sectors. The model simulates a dynamic baseline and it assesses changes from the baseline in response to changes in public policy or other factors affecting the sector (FASOM 2010). FASOM GHG distinguishes between 40 primary crop products, 27 processed crop products, 25 livestock products, 17 processed animal products, 12 forest and agricultural resides, 10 processing by-products, 32 timber products, and 40 processed forestry products (FASOM 2010). FASOM is developed with explicit land balances in each sector, endogenous prices for land and commodities, and constraints on land transfers based on land suitability. The dynamic framework allows for land transfer between sectors with land price equilibration within the sectors, based on the land's marginal profitability in all the alternative forest and agricultural uses across the time horizon of the model (Adams et al. 1996).

The FASOM-GHG is a modified enhanced version of FASOM specifically focussing on the environmental and economic impacts of public policies affecting the agro-forestry sector (FASOM 2010). This dynamic price-endogenous model identifies the allocation of land and other resources among competing activities, i.e. between and within the agricultural and forest sectors in the USA. The model provides a dynamic simulation of GHG emissions, prices, production, consumption and other environmental and economic indicators over an extended period of time, usually 40 or 100 years on a five-year time step basis.

Table 2.5. Highlights of the FASOM model: pros and cons.

Pros	Cons
A version designed for land use analysis exist	The model is complex to run and it requires expert knowledge
It is designed with explicit focus to maintain land balances in each sector, while modelling cross-sector land transfer	An exhaustive documentation is not available
	The model does not capture the iLUC effects
	The model is not publicly available
	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
	It does not avoid amortization to allocate LUC emissions over time

GLOBIOM

A model with specific focus on analysis for land competition is the Global Biosphere Management Model (GLOBIOM), developed by the International Institute for Applied Systems Analysis (IIASA) since 2007. GLOBIOM is a PE model with global coverage divided in 30 regions (GLOBIOM 2018). Regional versions of the model (e.g. GLOBIUM-EU, GLOBIUM-BRAZIL) with a higher spatial resolution of land covers and land uses allow assessing the LUC impact of regional policies (GLOBIOM 2018). Land cover maps describing the type of vegetation are drawn by the Global Land Cover 2000 (GLC 2000) database. The database provides harmonized land cover data over the whole globe, with data for plant characteristics, with a 1km resolution (GLC 2003) and 2000 as a reference year.

The land use information describes the type of production occurring on a specific land area (e.g. forest plantation, primary forest, eucalyptus plantation etc.) and they are mainly obtained from national census (GLOBIOM 2018). Inconsistencies between the land cover and use information are solved by using crop distribution maps. The spatially explicit Environmental Policy Integrated Climate Model (EPIC) is the part of GLOBIUM that determines the yields for all locations and crops included in the model (Figure 2.2). The EPIC framework distinguishes between yield achieved by different crop management systems and land characteristics in the spatial units, rescaled to fit the FAOSTAT average yields at regional level (GLOBIOM 2018). This is necessary to harmonize EPIC data with other parameters not supplied or other causes of yield mismatch.

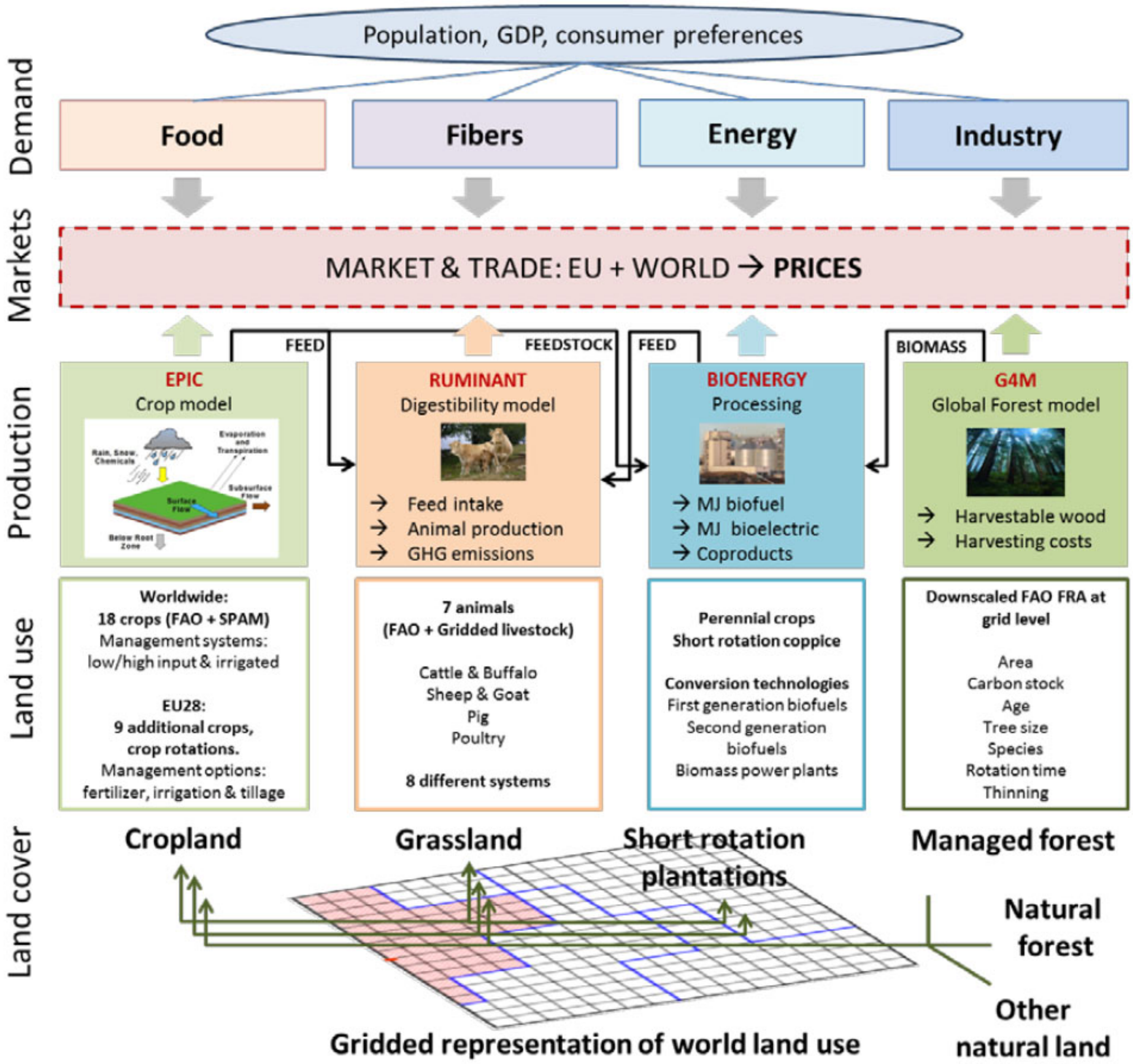


Figure 2.2 GLOBIOM modelling framework. Source: GLOBIOM (2018). The figure show the industries demanding land, the production models and the associated land use and land cover. This report does not describe in detail all the elements of the model presented in this figure. For a detailed description of the model, see GLOBIOM (2018).

As a PE model, the GLOBIOM model depicts a detailed representation of the agricultural sector (including crops and livestock), the forestry sector and the bioenergy sector, with a spatially explicit allocation of land uses and their respective carbon stocks and GHG flows. The model represents 18 crops globally, 27 crops for the European Union, with a specific focus on the representation of the production side (GLOBIOM 2018). The demand is represented by separated demand functions that do not take into account the total household budget and the relative substitution effects. Because the bioenergy sector is not included in the PE model, GLOBIUM includes the energy market's demand for bioenergy by linking to the CGE model MESSAGE, also developed by IIASA (GLOBIOM 2018). MESSAGE focuses on energy systems and it is used in conjunction with MAGICC (Model for Greenhouse gas Induced Climate Change) for calculating internally consistent (probabilistic) scenarios for climate change. The combination MESSAGE-GLOBIUM is known as an independent Integrated Assessment Model. Another Integrated Assessment Model with focus on land-using activities (IMAGE) is described in the section 2.2.

Table 2.6. Highlights of the GLOBIOM model: pros and cons.

Pros	Cons
The model is specifically designed for land-use analyses	The model is complex to run and it requires expert knowledge
The documentation is clear and accessible	It does not avoid amortization to allocate LUC emissions over time
The model is available in regionalised versions and it captures regional yield differences, accounting for the effect of climate change	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
It shows high spatial representation of land covers and land uses allow assessing the LUC impact of regional policies	It models a limited number of crops, although globally
It is available as part of a more complete Integrated Assessment Model (MESSAGE-GLOBIOM)	The model does not fully capture the iLUC effects unless it is coupled with the economic model MESSAGE, which makes the model an Integrated Assessment Model, increasing its completeness but also its complexity

MAgPIE

As shown so far, economic equilibrium models can consistently address the link between land, supply, demand and trade by endogenously determining prices. However, typically they do not embed physical resource balances or constraints. The Model of Agricultural Production and its Impact on the Environment (MAgPIE) is an open-source modular PE model of the land use sector with spatially explicit information on biophysical constraints within an economic decision-making process (Lotze-Campen et al. 2008). The MAgPIE approach provides more flexibility to integrate biophysical constraints into the economic models by linking physical and monetary units (Lotze-Campen et al. 2008). The development of the model began in 2008 but the most recent and fully open-source version of the model, MAgPIE v4, has been published in 2019 (Dietrich et al. 2019). The model contributed substantially to the IPCC assessments (Dietrich et al. 2019). MAgPIE is coupled with the energy-system model “Regional Model of Investments and Development” (REMIND). REMIND-MAgPIE represents an Integrated Assessment Model (Dietrich et al. 2019).

MAgPIE distinguishes between different crop types, including cereals, maize, rice, oilseed roots, and their management practice (irrigated and rained) and climatic conditions (temperate and tropical). It distinguishes between 20 cropping activities. Other than crops, the model includes 3 livestock activities, forest and other land types, including non-forest natural vegetation, abandoned agriculture and desert land. Crop yields are determined by the grid-based dynamic vegetation model “Lund–Potsdam–Jena dynamic global vegetation model with managed lands” (LPJmL). LPJmL links climate and soil conditions, water availability and plant growth, taking into account the effect of temperature, carbon dioxide concentration and radiation on yields (Lotze-Campen et al. 2008). LPJmL outputs also distinguish between changes in net primary production, changes in carbon pools, and water balances. LPJmL geographic grids distinguish between 12 economic world regions (Dietrich et al. 2019). MAgPIE use GTAP data on total cost of production (labour, chemicals and capital) divided by the total harvested area drawn from FAOSTAT to determine the average production costs per hectare for each production activity in each region (Lotze-Campen et al. 2008). MAgPIE estimates GHG emissions from LUC including the depletion of soil organic matter (MAgPIE 2019). The MAgPIE 4 framework (Figure 2.3) consists of 38 modules of which some are modified during simulations and other are static over time (Dietrich et al. 2019).

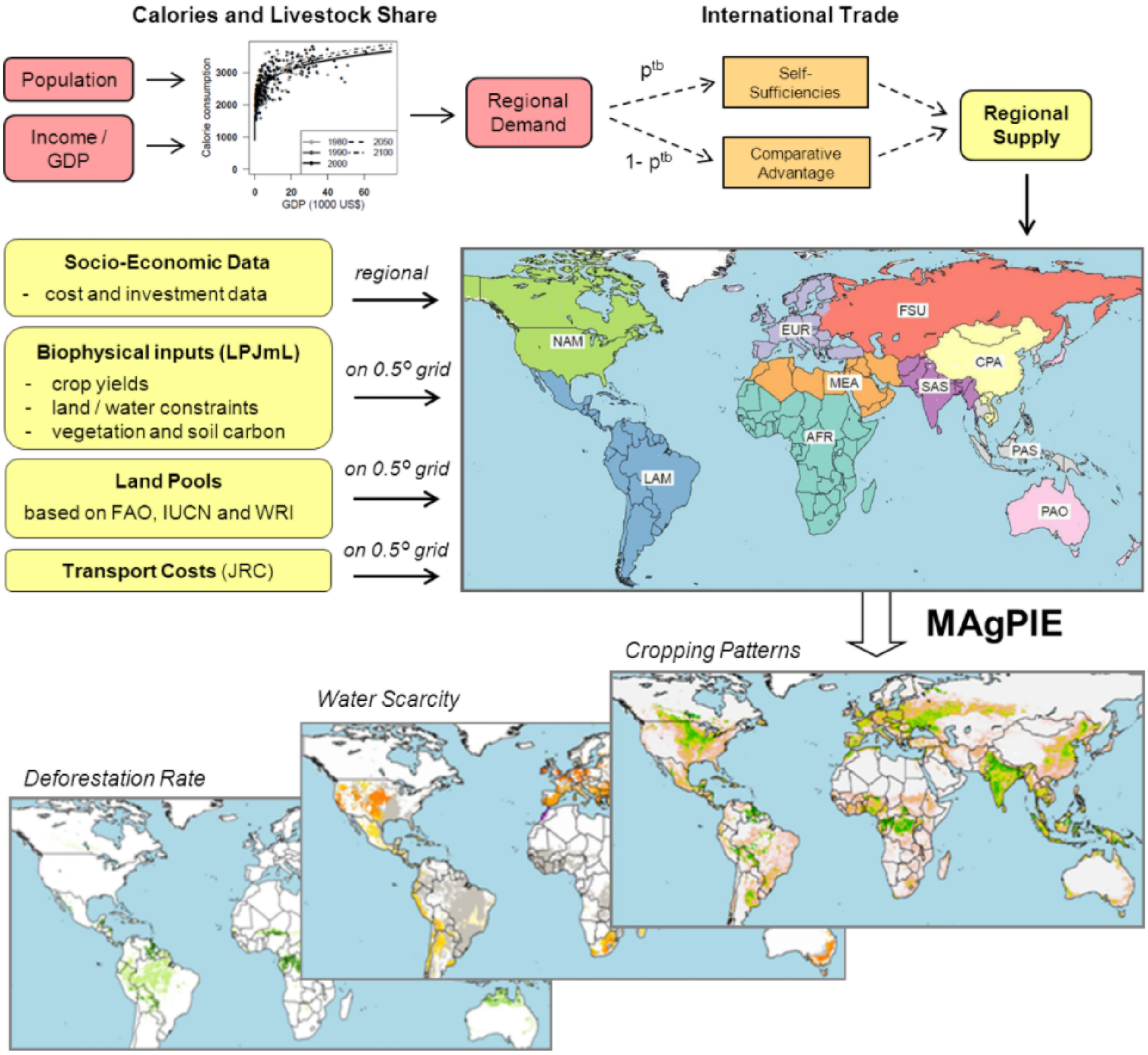


Figure 2.3 Simplified MAgPIE modelling framework. Source: PIK (2019). The flowchart shows key processes (demand and trade implementation, data inputs from LPJmL and the calculated spatially explicit water shadow prices). The model uses exogenous data about population and GDP development to calculate regional demand and the livestock share, which is then translated to regional supply depending on the international trade scenario. Socioeconomic data like production costs and biophysical inputs are obtained from LPJmL. After the optimization, one of the MAgPIE outputs is cropping patterns for different crops, which is the then used for the calculation of water shadow prices (PIK 2019). For a detailed description of the model, see (MAgPIE 2019).

Table 2.7. Highlights of the MAgPIE model: pros and cons.

Pros	Cons
The model is composed by modular open-source blocks allowing to include more accurately biophysical constraints into economic models	The model is complex to run and it requires expert knowledge
It is well documented and reproducible	It does not avoid amortization to allocate LUC emissions over time
It is specifically designed for analyses of the land-using sectors	It does not avoid amortization to allocate LUC emissions over time
It is available as a more complete Integrated Assessment Model by integrating an energy-system model (REMIND-MAgPIE)	The model does not fully capture the iLUC effects unless it is coupled with the economic model MESSAGE, which makes the model an Integrated Assessment Model (REMIND-MAgPIE), increasing its completeness but also its complexity

2.2 Causal-descriptive models (CDM)

CDMs describe future states of a system based on cause-effect relationships. These can be determined from a combination of biological and physical land characteristics, own and cross-price elasticities, statistical data, etc. CDMs tend to be simpler than economic equilibrium models (Nassar et al., 2011), reducing the computational effort and data requirement, and they appear conceptually easier to communicate. CDMs do not necessarily exclude economic aspects that drive the supply/demand patterns; rather, they forecast future production and consumption patterns based on current market trends and assumptions on agricultural supply/demand trajectories. Based on this, future land uses and their geographic origin can be estimated. Several CDMs have been developed to account for case-specific LUC-related impacts, e.g. Bauen et al. (2010), while flexible frameworks that are more generic are rare. Here we provide a detailed description of three CDMs with flexible generic framework, applicable do different crops and locations for different type of analysis, while we only include Bauen et al. (2010) as an example of model developed for a specific application, i.e. accounting for the iLUC effect of biofuel production in the UK.

2.-0 LCA iLUC model

The 2.-0 iLUC model is a CDM developed in 2011 and now available in its version 4.3. The model provides data for Life Cycle Assessment (Schmidt et al. 2015 www.lca-net.com/clubs/iluc/) and supports the calculation of direct and indirect LUC in Life Cycle Assessment (LCA). It is based on the principle that it is the additional aggregated demand for land that causes indirect LUC, which can involve both land transformation and land intensification (**Figure 2.4**).

The advantage of the 2.-0 LCA iLUC model is the simplicity with which it can be linked to customised LCAs of specific commodities and services, a characteristic that is not found in other approaches (De Rosa et al. 2016). In LCA, GHG emissions from LUC are often not correctly addressed: the most common approach is to allocate emissions from LUC over an arbitrary period of time as suggested by the normative models described below in section 2.3. This means that iLUC and causal links between land use and deforestation are typically disregarded in LCA models. By instead using the empirically determined increasing deforestation trend as its basis, the 2.-0 LCA iLUC model avoids this temporal allocation, and calculates the resulting Global Warming Potential from the land occupation of each specific year relative to the currently recorded deforestation trends (**Figure 2.5**).

The model describes the causal link between land demand and LUC, using land productivity data to describe the global market for the production capacity of land (Schmidt et al. 2015). The global market for arable land has inputs of both new arable land brought into production (accelerated land transformation) as well as intensification of the arable land already in production. The model distinguishes different market segments for different potential land uses, e.g., a market for arable land, a market for forest land, and a market for rangeland. To make arable land in different regions of the world comparable, they are weighted with a productivity-weighting factor, which is calculated as the occupied land’s potential net primary production (NPP_0) relative to the global average NNP_0 of arable land. When land occupation in ha*year are weighted by the productivity weight (PW), the land is converted into ha*year equivalents (ha*year-eq.). This framework is applicable to any land use and crop, and it is location agnostic.

Appendix 3 provides the PW factors used in the 2.-0 LCA iLUC model, for arable land, forest land and rangeland, for all countries/regions in the world. These factors describe the potential productivity of a certain land use type in each country, normalized to the global average potential productivity of that type of land use, thus making land in different countries comparable. E.g. 1 ha*year arable land in Indonesia corresponds to 1.96

ha*year-eq., where 1 ha*year-eq. is defined as global average arable land. The concept is described in Schmidt et al. (2015) and Schmidt and De Rosa (2018).

The model is integrated in the Hybrid Multi-Regional Input-Output (HMRIO) database EXIOBASE (Schmidt and De Rosa 2018). The production capacity in unit of hectare equivalent supplied by each country is accounted, distinguishing between productivity achieved by land transformation and by agricultural intensification, which have different environmental impacts. EXIOBASE's HMRIO data allow linking the production trends with the land use trends in each country (Schmidt and De Rosa 2018). For each land transformation and land intensification activity, the model links the respective data on carbon stocks and fertiliser use for different land use types in each of the 47 countries and regions in EXIOBASE. Fertiliser use data are drawn from the International Fertiliser Association.

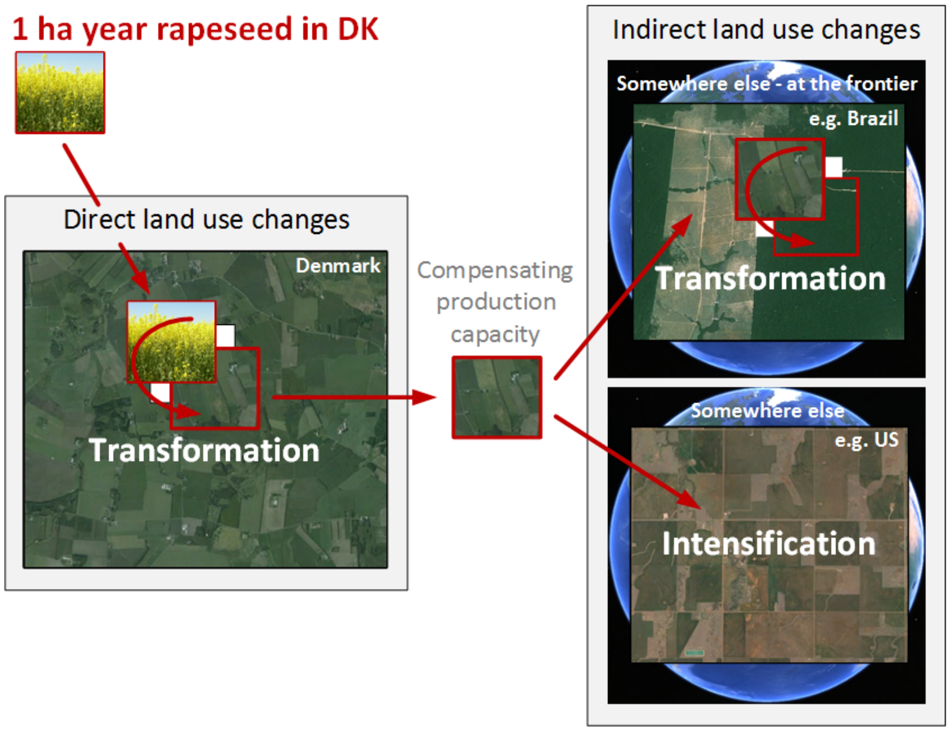


Figure 2.4 Illustration of the effects of adding a demand for land in Denmark of one hectare*year. The effects include indirect transformation of land and intensification to compensate for the production capacity in Denmark that is now no longer available due to being occupied by the new demand.

In the 2.-0 LCA iLUC model, the IPCC global warming potential (GWP) approach is applied also to also account for the different timing of emissions (Schmidt et al. 2015), as shown in **Equation 1** for a timing Δt (relative to a reference time t=0) for a substance *i*; see also **Figure 2.5**.

Equation 1

$$GWP_{i,\Delta t} = \frac{\int_{\Delta t}^{TH} RF_{i,\Delta t}(t - \Delta t)dt}{\int_{0}^{TH} RF_{CO2,t=0}(t - \Delta t)dt}$$

where:

$GWP_{i,\Delta t}$ is the global warming potential for substance *i* emitted at time Δt relative to t = 0

TH is the applied time horizon

$RF_{i,\Delta t}$ is the radiative forcing for substance *i*, emitted at time Δt relative to t = 0

$RF_{CO2,t=0}$ is the radiative forcing for CO_2 emitted at time t = 0

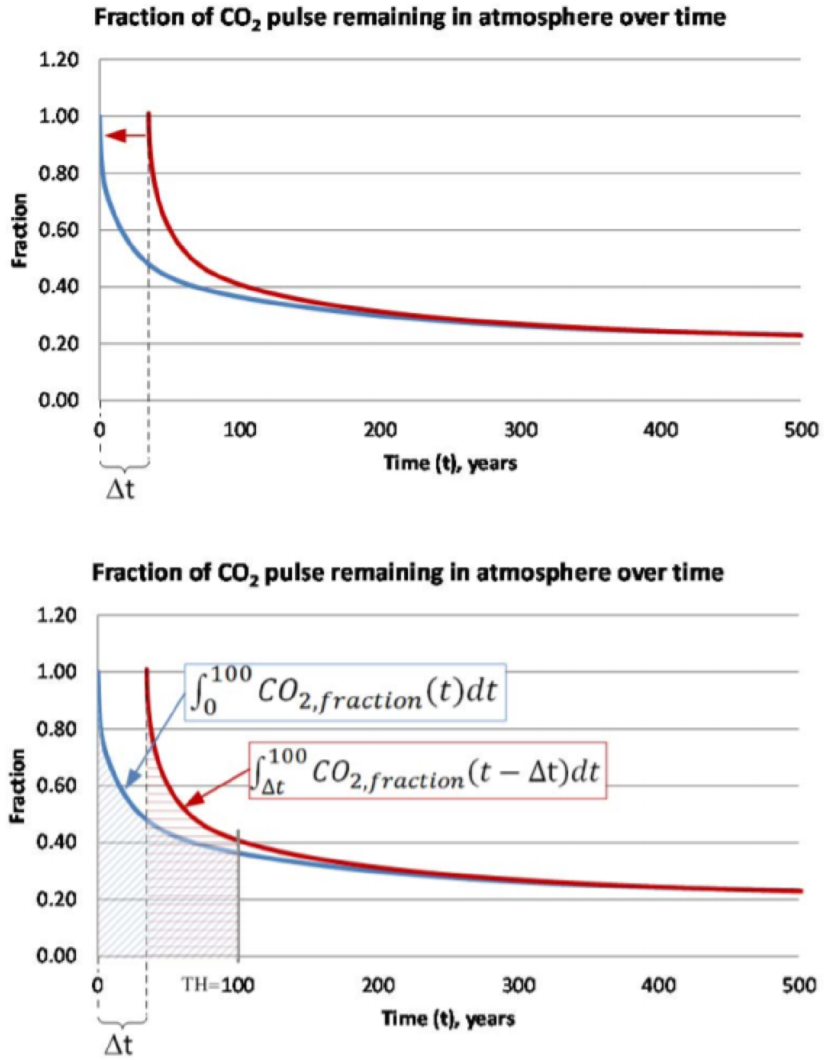


Figure 2.5 Top: Effect of emitting a CO_2 pulse at time Δt is illustrated as moving the CO_2 decay curve to the right. Bottom: The denominator in Equation 3.4 is illustrated as the blue shaded area (CO_2 emitted at time 0), and the nominator is illustrated as the red shaded area (CO_2 emitted at time Δt). (Schmidt and Brandao 2013)

Currently, version 4.3 of the 2.-0 iLUC model includes as elementary flows emissions of CO_2, N_2O, NO_x, NO_3^- , NH_3, accelerated CO_2 emissions (reflecting the effect of preponing the LUC by increasing the land demand), and resource inputs of accelerated denaturalisation caused by transformation of land. The model can be used with any impact assessment method, although the impact on nature occupation, measuring biodiversity loss, is only accounted with the Stepwise impact assessment method (Stepwise 2019). The impact assessment model shall also account for the temporal effects of CO_2 emissions.

Table 2.8. Highlights of the 2.-0 LCA iLUC model: pros and cons.

Pros	Cons
The model is publicly available and, although it is not free, the license cost is accessible	The model is not freely available and it requires a license
The model is applicable to any location and land use type	The simplicity of the model results in a lower level of detail in the representing the global economy compared to more advanced (yet much more complex) economic models
It is simple to operate despite capturing both economic and biophysical cause-effect relationships	The model documentation could be more detailed (note: a user manual is available)
It is specifically designed for commodity-base LUC analysis, and it is suitable also for small-scale analysis of specific production systems	The model is not designed for large-scale policy analyses.
It avoids the use of amortization to allocate LUC emissions over time by implementing an explicit temporal modelling of the climate effect of LUC	
The model can be easily linked to suitable life cycle impact assessment models to calculate commodity-based footprints	

IMAGE

As discussed previously in the context of CGE models, the integrated assessment model IMAGE initially integrated the CGE model LEITAP and currently the MAGENT model. MAGNET (Woltjer et al., 2011; Woltjer et al., 2014) is based on the standard GTAP model (Hertel, 1997) which is a multi-regional, static CGE. Developed by the PBL Netherlands Environmental Assessment Agency since 1990, the current IMAGE 3.0 addresses large-scale complex environmental and sustainable development issues for policy and decision-making (IMAGE 2014).

IMAGE integrates complex economic and biophysical earth system models, which make it one of the most detailed IAM for land-use analyses (IMAGWE 2014). The model has been applied to provide inputs to several global environmental assessments. Some of these are the Millennium Ecosystem Assessment (MA 2005); OECD Environmental Outlook to 2030 (OECD 2008) and to 2050 (OECD 2012); the UNEP Global Environment outlooks 3 (UNEP 2002) and 4 (UNEP, 2002; UNEP/RIVM, 2004); the IPCC Assessment Reports AR4 and AR5, with global mitigation scenarios (Van Vuuren et al., 2007). The IMAGE framework links multiple models to describe the functional relationships between human activities and their impact, including several modules accounting for the human system, the earth system, and their interaction (**Figure 2.6**). The IMAGE framework includes information generated by other detailed agro-economic models such as IMPACT and MAGNET as well as biophysical impacts generated by GLOBIO for the biodiversity model (IMAGE 2014). Compared to other Integrated Assessment Models that often only include climate change indicators, IMAGE shows a relatively detailed description of the biophysical processes, with a specific focus on land cover and land uses, and a wide range of environmental indicators, including climate and agricultural impacts, terrestrial biodiversity, land degradation and ecosystem services (**Figure 2.6**). IMAGE distinguishes 26 world macro-regions, some of which correspond to the largest countries. Land use, land cover, and associated biophysical dynamics are treated at grid level (10x10 km at the equator) to capture local dynamics.

The latest version (IMAGE 3.0) incorporates additional modules. The forestry management module models the forest production system, distinguishing management practices per region. Nutrient balances are established for both natural and productive land uses. A specific module simulates plant growth as a function of local conditions (soil, water climate etc.) and the associated carbon stocks and fluxes. IMAGE 3.0 integrates a recently updated climate model (MAGICC 6.0). The energy demand modules account for the energy demand of households, for urban or rural population and per income level, and the energy demand of energy-intensive industries.

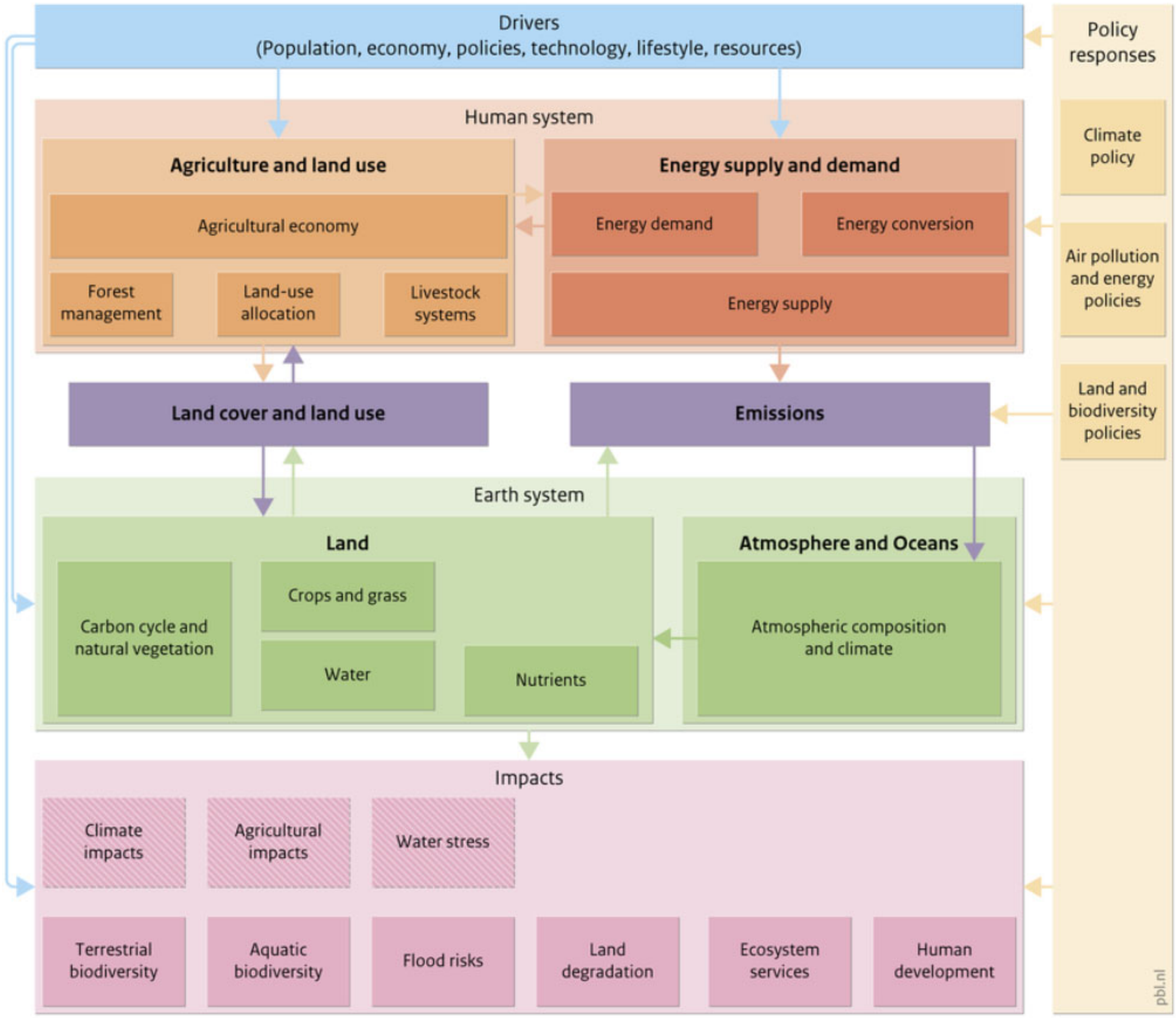


Figure 2.6 MAGE modelling framework. Source: IMAGE (2014). Obtained from PBL Netherlands Environmental Assessment Agency. The figure shows the information flow from the key driving factors to the impact indicators. This report does not describe in detail all the elements of the model presented in this figure. For a detailed description of the model, see IMAGE (2014).

Table 2.9. Highlights of the IMAGE model: pros and cons.

Pros	Cons
The model is publicly and freely available	The model is complex to run and it requires expert knowledge
The documentation is clear and exhaustive	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
The model is specifically designed for land-use analyses	It does not avoid amortization to allocate LUC emissions over time
A recent version integrates a climate model	

GlobAgri-WRR

A CDM largely based on biophysical relationships rather than on economic data is GlobAgri-WRR. GlobAgri-WRR is a version of the biophysical GlobAgri model developed by CIRAD, INRA, World Research Institute (WRI), and Princeton University. The World Research Institute used GlobAgri-WRR for the 2019 Word Resource Report (WRI 2019, Appendix A). This model does not include economic feedback effects of policies or scenarios. Rather, it focuses mostly on quantifying the land-use demands and the related GHG emissions from agricultural production up to farm gate. The model incorporates other biophysical models to account for the GHG emissions and land-use demands in specific agricultural sectors. Land-use requirements for crops and livestock production depend on yields figures from FAOSTAT. GlobAgri calculates the emissions from land uses applying a model developed by the European Commission's Joint Research Centre (JRC). The model estimates the GHG emissions caused by direct LUC for a determined crop area, depending on the type of crop and its location. This is done by identifying the areas of suitable land for each specific crop that is currently not in production yet, based on the GAEZ/FAO model. The model assumes that the cropland expands into the remaining ecosystems in proportion to their remaining availability of suitable land. A similar approach is applied for grazing land (WRI 2019, Appendix A). The emissions are then calculated based on IPCC emission factors. However, the major limitation of the GlobAgri-WRR model is that indirect LUC or land leakage effects are not accounted by the JRC's LUC model, which GlobAgri-WRR applies (De Rosa et al. 2016).

Table 2.10. Highlights of the GlobAgri-WRR model: pros and cons.

Pros	Cons
The model was explicitly designed for land use analysis	The model is not publicly available and a detailed documentation is not available, i.e. it is not easily reproducible or applicable
It distinguishes between yields depending on land location	It is not specifically designed for commodity-base LUC analysis; it is mostly applied for large-scale policy analyses
	It does not avoid amortization to allocate LUC emissions over time
	It does not capture the iLUC consequences
	It does not model any economic or market mediated effect

A regional, case-specific CDM

Other CDM for assessing the impact of LUC exist, often developed for specific case studies. The approach developed by Bauen et al. (2010) is one of these. The model was commissioned by the UK Department of Transportation specifically to account for the iLUC effects of introducing biofuels in the fuel mix of the transport sector, analysing five different biofuel types. This means that this model is restricted to a regionalised analysis of the biofuel sector. The model is the result of a participatory approach, aiming at achieving transparency and inclusion of stakeholders through a stakeholder consultation. The reason for this choice was to attempt a more democratic approach and to make the decision-making process more accessible to several parties than what the application of economic equilibrium models would guarantee. The authors relied on FAOSTAT statistics, the FAPRI dataset and the USDA Foreign Agricultural Service. To classify land, Bauen et al. (2010) applied Winrock International's estimation of historical land use change over the period 2001-2007, obtained with MODIS satellite data. A limitation of this model, common to several small-scale models, is that the origin of the marginal land supplying the additional productive capacity is not spatially identified (De Rosa et al. 2016).

Table 2.11. Highlights of the Bauen et al. (2010) model: pros and cons.

Pros	Cons
The model is specifically designed for commodity-base LUC analysis	The model is designed for a specific application and therefore it is not readily applicable to other scenarios
The model captures the immediate iLUC consequences	It is not applicable to all kind of crops and locations
It is based on a participatory approach and involved a stakeholder consultation	It does not avoid amortization to allocate LUC emissions over time
	Does not capture the global marginal ILUC consequences

2.3 Normative Models

Normative Models attempt a simpler approach to account for the LUC emissions, often based on statistical data (Audsley et al., 2009). NMs do not account for iLUC because iLUC emissions cannot be described by a general normative rule. Thus, NMs de facto avoid the most controversial aspect. This may be the main reason that they are often chosen in small-scale, product-specific environmental assessments. In addition, two frameworks commonly used in LCA follow this approach: the Publicly Available Specification (PAS2050 2011) and the Product Environmental Footprint (PEF) guide (European Commission, 2014).

PAS2050 (2011) provide guidelines for assessing the life cycle GHG emissions of goods and services, including LUC-driven GHG emissions. The method has also been applied by the EU's PEF guide (European Commission, 2014) and the GHG protocol (WRI/WBCSD, 2011). The GHG Protocol is a multi-stakeholder partnership of businesses, non-governmental organizations, governments, and others convened by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). The protocol suggests a standardized framework to measure GHG emissions from private and public sector, value chains, and mitigation actions. Yet, the GHG protocol does not include iLUC emissions and "*does not include consensus methods for sequestered carbon quantification. Companies should, therefore, explain the methods used*" (GHG protocol 2015). These frameworks made the PAS2050 NM approach widely used by LCA practitioners. A recent survey from the Word Resources Institute (WRI) found that there is a high demand for additional guidance in the GHG Protocol concerning the accounting of emissions from LUC, natural removal of carbon sequestration in biomass, and related to bioenergy (GHG protocol 2019). The demand for clarification especially concerns the accounting of GHG emissions and removal from agriculture, forestry, and other LUC and bioenergy.

The LUC accounting method suggested by Quantis (Quantis 2019) is the result of a stakeholder consultation. Although the guideline acknowledges the importance of iLUC, it does not recommend any methodology to account for iLUC and the topic is listed among the topics under discussion. The methodology recommends accounting for all the carbon pools, including above ground, below ground, and soil carbon, and to allocate the GHG emissions over a period of 20 years. The Quantis guideline recommends to temporally differentiate the allocation of the full amount of emissions when allocating the impact over time, i.e. allocating more emissions to production activities temporally closer to the LUC event and gradually assigns less impact to land uses occurring later. Yet, this is indicated as an option and the decision to perform this temporal differentiation or not is left to the practitioner.

Flynn et al. (2012) proposed a NM based on the IPCC national GHG inventory methodologies to assess LUC impacts from crops. The model is applicable when complex spatial models and detailed agro-economic information are not available, for example for small-scale studies or in developing contexts, or when information on crop origin and growing conditions is limited. The model allows the conversion of unit area emissions from LUC from hectares to tonnes on a product basis (Flynn et al., 2012), but the analysis is restricted to the top 20 producing countries of the assessed product, and a single yield value is assumed for each country.

A normative approach is adopted for calculating a LUC factor for biofuel production by Fritsche et al. (2010): 25% of production is assumed as coming from intensification of land already in use or "set free" land, with a zero displacement risk, and 75% from "new land" responsible for iLUC effects.

Table 2.12. Highlights of normative modelling approaches mentioned above: pros and cons.

Pros	Cons
The models are very simple and easy to apply	The models do not capture iLUC consequences
They are applicable to different crops and location	They do not avoid amortization to allocate LUC emissions over time. They explicitly suggest to allocate GHG emissions over an arbitrary period of time (typically 20 or 25 years)
They are applicable to commodity-based LUC analysis	They do not capture the effects of intensification and deforestation to obtain the biomass production capacity
	They do not include economy-wide models or economic data
	They do not account for the effect of occupying land with different productivity

2.4 Assessment of the models

The presentation of the models in the previous section does not intend to be exhaustive. The brief introduction of the models is intended as an overview of the main characteristic but it is not sufficient to capture the complexity of the models and to identify their key differences. In order to provide an overview of the principal characteristics and differences between the models, the criteria shown in **Table 2.13** have been applied. The criteria are formulated as a statement. They assess the applicability and transparency of the model and their key methodological aspects. A 'X' in **Table 2.13** indicates that the statement is valid for a model. A "-" indicates that the statement is not valid for the model. "n.a." indicates that the statement is not applicable to the model. The background information for the model assessment and comparison in **Table 2.13** can be found in Appendix 1.

Table 2.13 Evaluation of the models. 'X' indicates that statement of the criterion applies to the model; "-"indicates that the statement of the criterion does not apply to the model; "n.a." indicates that the criteria is not applicable to the model; "?" indicates that no information was identified. Compared to **Table 2.1**, MAGNET is excluded because it is integrated in IMAGE. LEITAP is excluded because it has been replaced by MAGNET. FARM is excluded because based on an early version of GTAP (Darwin et al. 1995, p 45).

	Economic Equilibrium Models (EEM)							Causal descriptive models (CDM)				Normative models (NM)		
Criteria	**CAPRI**	**FAPRI-MU**	**FASOM**	**GLOBIOM**	**GTAP-AEZ**	**IMPACT**	**MAgPIE**	**2.-0 LCA iLUC**	**GlobAgri-WRR**	**IMAGE**	**Bauen et al (2010)**	**Quantis LUC model**	**PAS 2050**	**GHG emission protocol**
Applicability and Transparency														
The model can be operated by other than the developing institute	X	-	-	X	X	-	X	X	-	-	X	X	X	X
The model is publicly available	X	-	-	X	X	-	X	X	-	X	-	X	X	X
The model is freely available	X	-	-	X	-	-	X	-	-	X	-	X	X	X
The documentation is accessible and it allows to reproduce the model	-	-	-	X	-	-	X	X	-	X	X	X	X	X
The model applies to all kinds of demand for land (all crops, forest products, other land uses)	-	?	-	-	-	-	-	X	-	-	-	X	X	X
The model has a global geographical coverage	-	?	-	X	X	X	X	X	X	X	X	X	X	X
Methodology														
The model captures the cause-effect link between the land demand and dLUC and iLUC	-	-	-	X	X	-	X	X	X	X	X	-	-	-
The model avoids amortization to allocate LUC emissions over time	-	?	-	-	-	-	n.a.	X	-	n.a.	-	-	-	-
The model includes deforestation and intensification to provide land production capacity	-	?	X	X	X	X	X	X	-	X	X	-	-	-
The model assumes full elasticity between land demand and supply	-	?	-	-	-	-	-	X	?	X	X	?	X	X
The model is linked to an economy-wide model (such as input-output or EEM)	X	?	X	X	X	X	X	X	-	X	-	-	-	-
The model distinguishes between land-use types based on land productivity or similar	X	?	X	X	X	X	X	X	X	X	X	-	-	-

The table shows a broad variability in the performances of the models assessed. This is due to the fact that not all of these models are specifically designed for land-use analyses and not all models are designed for accounting for commodity-driven LUC. Not surprisingly, the most recent models with specific focus on global LUC analysis show better performance. Among the economic equilibrium models, the best performing models are GTAP-AEZ and MAgPIE, both specifically intended for LUC assessments. The models are based on large collaborative efforts and they are continuously updated. Among the causal descriptive models, the 2.-0 iLUC model and IMAGE are the most complete models. The 2.-0 LCA iLUC model (Schmidt et al. 2015) appears to be the most competitive within the scope of the assessment, i.e. quantifying commodity-driven LUC, as the model is specifically designed for product-based environmental Life Cycle Assessment (LCA).

The normative models do not support iLUC analyses because they do not capture the cause-effect link between product demand/supply and iLUC. In fact, they are normative allocation approaches rather than models: they provide recommendations and guidelines for accounting dLUC in a simplified and straight forward manner. For this reason, they have obtained wide-spread application in companies that apply carbon footprint reporting. It is important to stress that normative models exclude land leakage effects from the LUC accounting. The Quantis model, the most recent normative approach proposed, is the only one that acknowledges the importance of accounting for iLUC but without providing any guideline about how to do it, seemingly due to lack of consensus among the stakeholders.

A key distinction between the models in **Table 2.13** is their intended purpose. GTAP-AEZ, MAgPIE and IMAGE are models designed for large-scale and long-term policy analysis, scenario simulations and forecasting. They are based on economic equilibrium models but integrate a number of tools and model that address specific issues such as climate models, water models, geographical models, land productivity and suitability based on the agro-ecological zones, etc. Yet, the high level of detail compromises their reproducibility and accessibility and it also makes their documentation less accessible and their configuration less transparent. These models are typically developed by collaborative efforts among research institutions that set up the model to run simulations tailored to an analysed scenario. Models such as the 2.-0 LCA iLUC (Schmidt et al. 2015) and Baunen et al. (2008) model are less computationally intensive and more straight-forward, while they do not renounce on capturing the complexity of global LUC mechanisms. This is reflected in the fact that their documentation is more accessible and the model more transparent. Baunen et al. (2008) was developed for a specific analysis and the model was not made available, i.e., it is not possible to reuse it with different scope unless the entire model is reproduced. The 2.-0 iLUC model (Schmidt et al. 2015) is applicable to any crop and location worldwide and it is designed to generate inventory data directly to be applied in environmental LCA. This means that, coupled with compatible Life Cycle Impact Assessment models, the 2.-0 iLUC model generates LUC-related impact assessment results, including global warming and biodiversity loss, as well as other conventional LCA impact categories, such as eutrophication, acidification, toxicity, etc.

It should be noted that a potential incongruence may rise between economic models and LCA applications (De Rosa et al. 2016): Models based on economic equilibrium analysis account for fluctuations of market prices based on elasticity functions which capture short-term inelasticity of the supply due to e.g. market shocks or sudden physical constraints (often causing market shocks). In LCA applications instead, it is common practice to assume full elasticity of supply because LCA analysis focus on long-term effects, assuming that, in the long run, all the demand is met. At the same time, the consequential LCA approach also models market substitutions among products. In conclusion, the 2.-0 iLUC models seems to reach an acceptable compromise between model complexity and applicability, without compromising reproducibility and completeness of scope (De Rosa et al. 2016).

Key recommendations to model LUC:

- In order to avoid burden-shifting and thus misleading conclusions, models accounting for LUC impacts shall always include both dLUC and iLUC. Trade-offs exist between model complexity and detail on one hand and applicability and transparency on the other hand. However, complexity should not be reduced by providing an incomplete and misleading model of the reality.
- The model applied to quantify LUC-related impacts shall be consistent with the scope of the analysis within which LUC are accounted for. In particular:
    - Commodity-based analyses of LUC-related impacts should apply LUC models based on product life-cycle thinking, such as the 2.-0 LCA iLUC model. An LCA approach typically seeks to model the long-term, prospective impacts of small demand changes in a stock-flow-consistent and demand-driven economy.
    - Detailed large-scale analyses attempting to simulate or predict the LUC consequences of land-use policies should prefer advanced and transparent models designed for this purpose, such as: IMAGE, GTAP-AEZ, MAgPIE or GLOBIOM. These models typically account for the effect of larger perturbations in a short-medium term parameterised economy with supply-constrained market equilibria.
- The LUC model applied should be either suitable for the intended land use and geography or applicable to any land use and geography. Models such as the 2.-0 LCA iLUC model are applicable for any land-use type and location.
- Normative models are based on norms and conventions. They do not account for iLUC and are typically used to comply to specific guidelines or standards rather than for gaining comparative insights aimed at supporting decision-making processes to reduce impacts from LUC.

3 Land use and tropical deforestation: three iLUC cases

This chapter discusses three cases of indirect land use change, to make a critical assessment of deforestation free commodities. The first case discusses the effect of a palm oil certification scheme in mitigating the iLUC impacts. It shows that certification may support no-deforestation commitments for products with complex supply-chains such as palm oil. The iLUC GHG emission reduction achieved with the RSPO certification scheme is quantified using the 2.-0 LCA iLUC model (section 2.2). The second case shows how the 2.-0 LCA iLUC model can be applied to make a simple screening assessment of the potential iLUC effect of a sustainable land-use initiative. The third case shows how trade data and geographical information can be used to verify claims of GHG emission reduction caused by soybean crops in Brazils. The assessment is performed using the concepts of iLUC modelling.

Tropical deforestation is mainly a consequence of the continuously increasing demand for bio-based products and the fact that most of the temperate forest has already been converted to agricultural land in the previous centuries (FAO 2012). The global production of agricultural commodities is increasingly relying on tropical countries. Export from tropical regions is strongly linked to emerging economies, suppling almost every country in the world (Trase 2018). This is particularly true for the so-called flex crops, crops that gained market appreciation due to their versatility, such as oil palm, soy, sugarcane and maize. In 2017 most of these crops were produced by a handful of countries: more than 80% of the palm oil production occurred in Indonesia and Malaysia; more than 80% of the soybean production occurred in the United States, Brazil and Argentina. Brazil produced alone almost half of the global sugarcane (FAOSTAT 2019). The agricultural production represents a key economic input for the economy of tropical countries. However, this also results in an intense pressure on biodiversity and carbon-rich tropical forests, causing environmental and climate consequences that, in the end, could exceed by far the economic gains for the entire global economy and jeopardize the future of human and ecosystems existence. Below, we analyse the relationships between two of these products, palm oil and soybean, and their land use change effects. We discuss the iLUC implication linked to the expansion of these two crops. For the palm oil case, we use data from a recent study assessing the difference in environmental impact between RSPO-certified and non-certified palm oil in Indonesia and Malaysia (Schmidt and De Rosa 2019). For the soybean case, we use data from Trase and the Trase 2018 yearbook (2019). Trase uses biophysical, geospatial data and trade information to link direct and indirect LUC to commodities and their principal traders and producers in a determined region.

3.1 Zero-deforestation or reduced deforestation: the case of Palm oil certification

Claims of "no-deforestation" palm oil are often challenging to make due to several reasons. Among these are the complexity of the supply-chain, with multiple stakeholders both at the primary supply and final demand side and in the trade in between; the lack of a consensus-definition of "forest"; the limited leverage on and control of the supply-chain from downstream retailers; and the lack of institutional support (Lyons-White and Knight, 2018). The pressure of consumers and NGOs' campaigns for more sustainable palm oil has sparked the Roundtable on Sustainable Palm Oil (RSPO), a non-profit industry-led trade organisation established in 2004 to promote the production and use of sustainable palm oil.

Certification can be a reliable and verifiable means towards reducing deforestation in palm oil production (Lyons-White and Knight, 2018). Yet, certification may also be used in support of controversial no-deforestation claims. According to the recently revised RSPO's principles and criteria (P&C), land clearing for palm oil production shall "*(…) not cause deforestation or damage any area required to protect or enhance High Conservation Values (HCVs) or High Carbon Stock (HCS) forest*" (section 7.12.2, RSPO 2018a). This means that, in order to be granted certification, oil palm growers cannot clear land on HCV or HCS forest lands after November 15th 2018. Although this is a remarkable achievement, it should be made clear that avoiding deforestation of HCV and HCS forests does not mean that the commodity is necessarily deforestation-free, because other forest types or valuable ecosystems might be affected as indirect consequences of the HCV/HCS land protection (Lyons-White and Knight, 2018). The risk is that a claim of deforestation-free palm oil might be questioned by third parties due to land-leakage effects, with the result that the actual environmental benefit achieved by certification may be overshadowed and/or mistrusted.

Currently, linking trade data with geographical data allows to unveil much information on the complex palm oil supply-chain and to gain further insights concerning the indirect impacts of palm oil. This also means that claims of "deforestation-free" commodity are becoming more challenging to support. For example, the demand for RSPO-certified palm oil mostly originates from large companies in developed countries. They produce commodities with large market shares in these countries. The increasing demand of RSPO-certified palm oil in developed nations has increased their share of RSPO-certified palm oil and it may also increase the overall share of certified oil but this does not meant that RSPO certified oil does not cause iLUC or that it has any effect on the oil sourced by neighbouring developing countries. Currently, the neighbouring developing countries, such as China, India and Bangladesh among others, source the largest share of Indonesian palm oil (**Figure 3.1**).

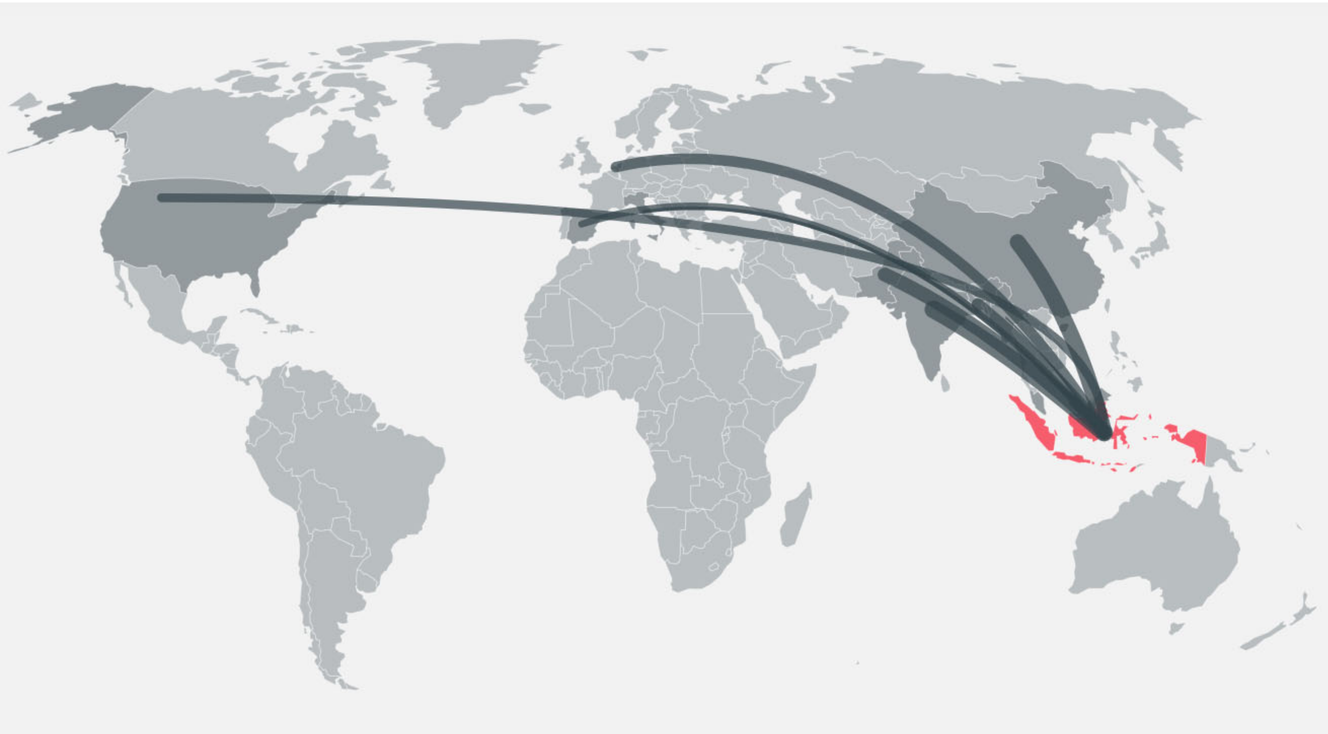


Figure 3.1 Trade volumes of palm oil in 2018 from Indonesia to the rest of the world. The top-ten sourcing countries are: India (23.7%), China (12.6 %), Pakistan (9.3 %), Bangladesh (4.9 %), Netherlands (4.1 %), US (3.6 %), Spain (3.5 %), Malaysia (3.5 %), Italy (3.3 %), Myanmar (3 %). Data and graphic obtained from trase.earth/explore (Trase 2019).

Since the neighbouring developing countries continue to import the remaining non-certified share of palm oil the iLUC effect of certification must be taken into account to avoid burden shifting. Even if all the palm oil was RSPO-certified, i.e. no-further HCV/HCS deforestation for palm oil production (section 7.12.2, RSPO 2018a), indirect LUC would not be avoided: other crops would be displaced from current agricultural areas or marginal non-HCV/HCS areas to make room to oil palm plantations. These displaced crops will have to be produced somewhere else, i.e. on the remaining land, causing deforestation of HCV/HCS areas. This shows the importance of accounting for iLUC and quantifying the benefits in terms of iLUC reduction achieved by RSPO-certification rather than advancing disputable claims of "no-deforestation" palm oil.

A recent study compared the life-cycle environmental impact of RSPO-certified and non-certified palm oil by performing for the first time a detailed LCA of the two production systems (Schmidt and De Rosa 2019). The study includes the iLUC effect, calculated with the 2.-0 LCA iLUC model (section 2.2), a model specifically designed for quantifying the iLUC effect when carrying out LCAs of products. This iLUC model resulted as one of the most relevant model among the ones compared in section 2.4. The study concluded that RSPO-certified palm oil reduces GHG emission by 35%, a reduction mainly achieved by increasing crop yields, thus requiring less land per unit of product, reducing the share of oil palm on peat soil, and increasing the share of palm oil mill effluents treated with biogas capture. The study also found that RSPO-certified palm oil reduces the nature occupation by 20% (Schmidt and De Rosa 2019), thanks to the higher yields of average certified oil palm plantations. The results are even more significant when comparing the iLUC contribution reduction: Because of the higher productivity of the RSPO-certified production system, the certification reduced the iLUC from 0.62 kg CO_2 eq./kg refined oil to 0.49 kg CO_2 eq./kg refined oil, a reduction of 21% of the iLUC GHG emissions (**Figure 3.4**). This reduction also includes the iLUC caused by nature conservation activities, i.e., from specific HCV land conservation activities.

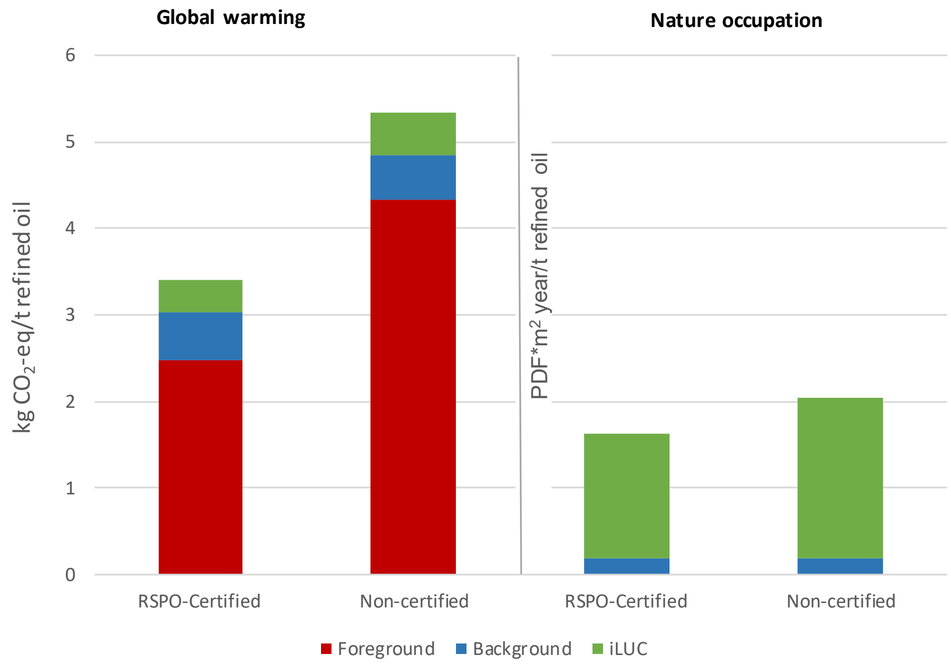


Figure 3.2 Contribution to results from foreground system (activities directly linked to the production of the commodity), background system (activities required for the production of the commodity), and iLUC contribution, for the global warming and nature occupation (biodiversity) impact categories (Schmidt and De Rosa 2019).

Lesson learned:

- "No-deforestation" claims depend on several factors such as the definition of forest and the quantification of iLUC effect of the commodity. Otherwise, these claims might potentially expose the commodity's producers to criticism or to become object of NGO's campaigns. There is also a risk that the evolving regulations may neutralize previous efforts or future attempts to undertake actions. Therefore, "no-deforestation" claims shall be supported by proof that land expansion occurs on land that is abandoned at the moment of the occupation, i.e. it is outside of the market of productive land, or that the net LUC effect is a net forest gain.

- Since indirect Land Use Change will almost certainly be triggered by production activities, the benefit of sustainable land use solutions can be better assessed by quantifying the actual impact reduction achieved, including the iLUC effect, rather than with qualitative "no-deforestation" claims.
- These impact reductions could be measured both in terms of GHG emissions (or emission reductions) and nature occupation, measuring the potential biodiversity loss (or avoided loss).
- The model applied for the quantification of the LUC effects triggered by the production activity should be able to quantify these impacts and should be chosen consistently with the goal of the assessment.

3.2 Sustainable Natural Rubber Plantations in Indonesia: iLUC-free?

In 2017 natural rubber plantations occupied almost 12 million ha globally. Indonesia, Thailand and Malaysia provided about 70% of this area. Indonesia was the single country providing the largest share of the harvested area (3.7 million ha), followed by Thailand and Malaysia (FAOSTAT 2019).

The PT Royal Lestari Utama Project (PT RLU) aims at developing a best-in-class sustainable land-use through the identification, set-aside and conservation of HCV tropical rainforest landscapes. The project involves three Industrial Forest Plantation concessions with a total area of 91,511 ha in the provinces of Jambi (two concessions for a total of 71,872 ha) and East Kalimantan (a concession of 19,639 ha), Indonesia (**Figure 3.3**).

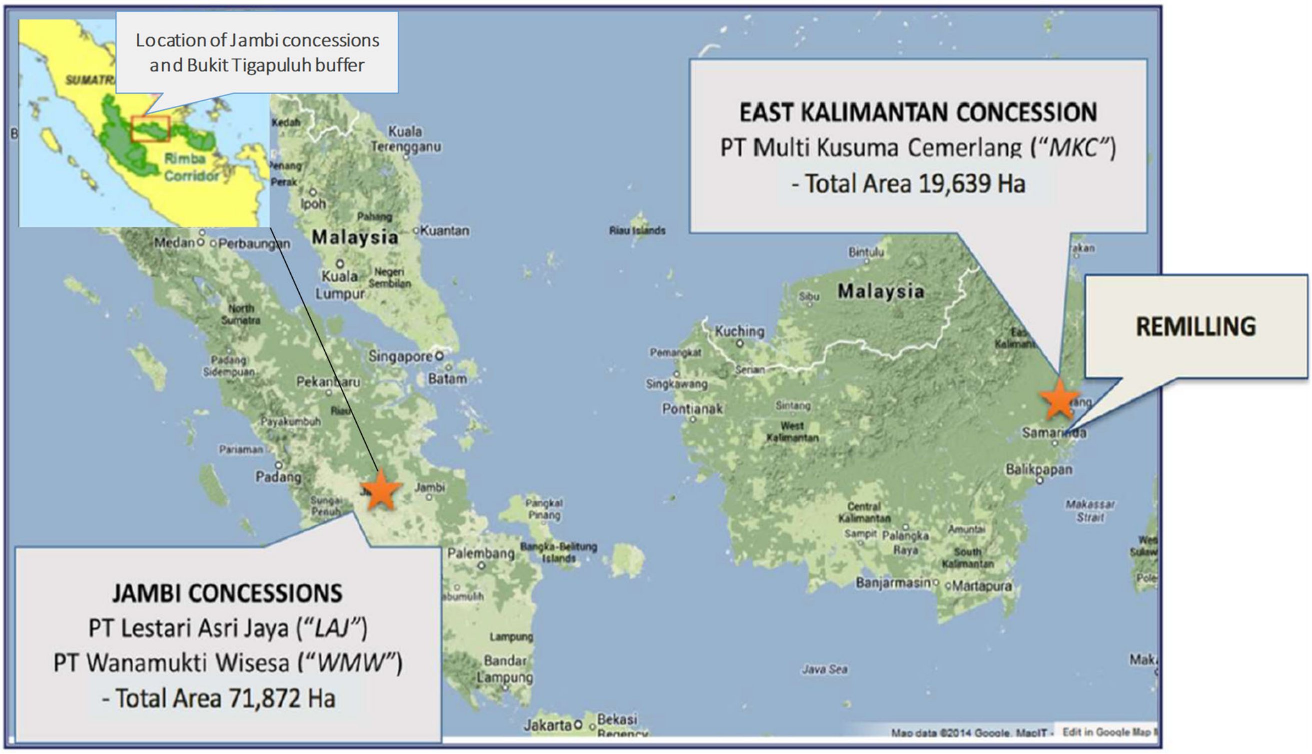


Figure 3.3 Overview of Jambi and East Kalimantan concessions location in the wider geographic context (PT RLU 2019).

The no-go areas delineated a total of 18.370 ha (26% of the total concessions) but currently, only 3.760 ha of the no-go area (5%), largely secondary forest, are intact. In Jambi, 8,200 ha of the RLU's protected zone are part of the Wildlife Conservation Area (WCA), strategically located adjacent to the Bukit Tigapuluh National Park (BTPNP). The WCA area provides a natural corridor for the wildlife linking two existing buffer zones. Only 3,761 ha of the Jambi's RLU total protected areas (18,370 ha) are currently intact forests (PT RLU 2019). In

Kalimantan, the total forest cover accounts for 7.822 ha (48% of the total) in a protected area of 9.983 ha. All of the concessions have suffered severe deforestation and degradation over the last two decades from illegal logging, slash and burn practices and illegal developments (PT RLU 2019).

Table 3.1 and **Table 3.2** provide an overview of the protected areas and restoration targets for the RLU's concessions in Jambi and East Kalimantan respectively.

Table 3.1. Forest conserved and restoration targets (ha) on the concession in the Jambi province, Indonesia. The "Protected areas under control by RLU (2033 target)" is the sum of the "Baseline Forest Cover (2016/2018)" and the "Restoration target". The total at the bottom of the table is the sum of the cells in black font above (PT RLU 2019).

Affected area	Description	Protected Area delineation (set asides)	Baseline Forest Cover (2016/2018)	Protected areas under control by RLU (2018 baseline)	Restoration target	Protected areas under control by RLU (2033 target)
JAMBI						
HCV/HCS	**HCV/HCS Total**	13,783	3,696	2,000	1,378	**5,074**
HCV/HCS only	HCV/HCS Outside the WCA area	9,150	1,207	0	624	**1,831**
HCV/SCS & WCA	HCV/HCS Inside the WCA area	4,633	2,489	2,000	754	**3,243**
WCA	WCA total	8,198	2,489	2,200	2,839	**5,328**
no HCV/HCS/WCA	Non-HCV riparian areas outside the WCA	917	0	0	917	**917**
Other	Other land types	104	0	0	104	**104**
TOTAL		**18,369**	**3,696**	**2,200**	**4,484**	**8,180**

Table 3.2. Forest conserved and restoration targets (ha) on the concession in East Kalimantan, Indonesia. The "Protected areas under control by RLU (2033 target)" is the sum of the "Protected areas under control by RLU (2018 baseline)" and the "Restoration target".

Affected area	Description	Protected Area delineation (set asides)	Baseline Forest Cover (2016/2018)	Protected areas under control by RLU (2018 baseline)	Restoration target	Protected areas under control by RLU (2033 target)
EAST KALIMANTAN						
HCV/HCS	HCV/HCS Total	9,375	6,422	6,500	531	**7,031**
Riparian areas	Riparian areas beyond HCV/HCS	1,802	1,400	1,400	402	**1,802**
Other	Other land types (occupied by smallholders)	608	0	0	122	**122**
TOTAL		**9,983**	**7,822**	**7,900**	**1,055**	**8,955**

Setting-aside land for restoration and/or conservation, can have a positive climate effect but it also generates iLUC because the lost productive capacity of the conserved or restored areas must be obtained from deforestation elsewhere or from agricultural intensification. The net climate effect can therefore only be assessed by including the iLUC effect. The 2.-0 LCA iLUC model (section 2.2) applied in the palm oil iLUC case in section 3.1 can also be used for calculating the iLUC in this example. In fact, the 2.-0 LCA iLUC model does not require a full LCA study but can also be used to calculate GHG emissions caused or avoided by land use activities simply based on data on the area affected by the LUC (the restoration target in **Table 3.1** and **Table 3.2**) and the different carbon stocks of the land use types before and after the changes. Other necessary input data are global default factors that can be drawn from tables (see section 4 and Appendix 3). If specific on-site carbon stock data are not available, the default carbon stock values in **Table 3.3** can be used (GAR-SMART

2012). The values in **Table 3.3** are not rigorous enough or technically sufficient for carbon accounting but could be used for screening the potential effects of a project dealing with similar land types and locations (e.g. Indonesian rain forest), if carbon stock estimates for the land object of the set-aside are not available (GAR-SMART 2012). The data on restoration targets in **Table 3.1** and **Table 3.2** and **Table 3.3** allow to calculate the GHG emissions or uptake due to nature conservation, net of the iLUC effect, using Equation 4 described in section 4.1 below. Assuming that the carbon of arable land is 5 t C/ha, the net effect of a restoration target setting aside one ha of old scrub (60 t C/ha **Table 3.3**) for 1 year is the net emissions due to iLUC. To achieve a net carbon uptake, it is necessary to ensure nature conservation for several years. Assuming an average uptake of 5 t C/ha, a net carbon sequestration would be achieved in this case after approximately 20 years. This means that one year of nature conservation/restoration achieved by the RLU project does not result in the natural rubber produced being deforestation-free. Ensuring long-term protection of forested land is necessary to offset iLUC emissions.

Table 3.3. Default carbon stock values of vegetation cover classes and vegetation cover classes definitions (GAR-SMART 2012).

Vegetation cover class	Code	Vegetation cover definition	Estimated carbon stock (average)
High Density Forest	HK3	Remnant forest or advanced secondary forest close to primary condition.	192 t C/ha
Medium Density Forest	HK2	Remnant forest but more disturbed than High Density Forest.	166 t C/ha
Low Density Forest	HK1	Appears to be remnant forest but highly disturbed and recovering (may contain plantation/mixed garden).	107 t C/ha
Old Scrub	BT	Mostly young re-growth forest, but with occasional patches of older forest within the stratum.	60 t C/ha
Young Scrub	BM	Recently cleared areas, some woody regrowth and grass-like ground cover	27 t C/ha
Cleared/Open Land	LT	Very recently cleared land with mostly grass or crops, few woody plants.	17 t C/ha

Nature restoration and conservation is not the only opportunity to reduce the environmental impacts of rubber production. The RLU project has also identified areas where the production of rubber can be improved by increasing land productivity. **Table 3.4** provides an overview of the target areas dedicated to increasing land productivity (intensification) for the RLU's concessions in Jambi and East Kalimantan respectively. The natural rubber yields in Indonesia (0.99 t/ha) are on average lower than the global average yields (1.21 t/ha) and especially lower than the average yields in Thailand (1.46 t/ha), based on FOSTAT data for 2017 (FAOSTAT 2019). Therefore, there is potential for improving land productivity.

Table 3.4. Land intensification targets (ha) on the concession in Jambi and East Kalimantan, Indonesia (PT RLU 2019). CPP: Community Partnership Programme; RLU: Royal Lestari Utama.

Agricultural Intensification	Baseline 2018	Target 2033
JAMBI		
RLU Rubber plantations	14,051	30,000
CPP Plasma smallholders	-	6,000
TOTAL	**14,051**	**36,000**
EAST KALIMANTAN		
RLU Rubber plantations	4,649	4649
CPP Plasma smallholders	-	1,000
TOTAL	**4,649**	**5,649**

Table 3.4 shows that the targeted area for land intensification in the concession located in the Jambi province is approximately 22,000 ha, of which 6,000 involve smallholders. In the concessions in East Kalimantan, intensification activities are planned for 1,000 ha involving smallholders.

The national average yields of natural rubber in Indonesia are 0.99 t/ha compared to a global average of 1.21 t/ha (FAOSTAT 2019). The highest national average is recorded in Thailand (1.46 t/ha). Based on Equation 5 in section 4.2, aligning the Indonesian yields to the global average yield of natural rubber would give a GHG emission reduction of 0.56 t CO_2/ha.

Lesson learned:

- iLUC can be reduced by nature conservation activities but a complete iLUC offset requires guaranteed nature conservation commitments for a long period of time, depending on the initial and potential carbon stock of the area targeted by the restoration project.
- When accounting for iLUC, it is clear that agricultural intensification provides an effective an immediate GHG emission reduction opportunity. In particular, when there are large margins for improving the national average yields, as in the cases of natural rubber production in Indonesia, the potential GHG emission reduction are significant.

3.3 Assessing of Brazilian Soy iLUC with geospatial data and trade information

During the last forty years, the growing of soy has increased nearly exponentially in South America: In 2017, Brazil, Argentina and Paraguay produced more than 50% of the soybean production globally, 95% of the Latin-American production; fifty years ago, they produced 3% of the global soy (FAOSTAT 2019). In 2017, Brazil alone accounted for 32% of the total global production, being the second largest supplier after the US (34%). Based on the current trends, Brazil will soon overtake the US. Argentina is the third largest soybean producer (15%). The steep increase in demand for soy is a response to the growing global meat consumption and partly also a consequence of the global concern for the bovine spongiform encephalopathy (BSE, better known as the “mad cow” disease) which led to soy largely replacing animal products in livestock feeds in the 1990s and 2000s (Trase 2018). Soy expanded rapidly during these years and it has now become the single largest most profitable export commodity in Brazil (World Bank 2019).

Figure 3.4 Trade volumes of Soy in 2017 from Brazil to the rest of the world. The top-ten sourcing countries are: China (47.2 %), domestic consumption (26.7 %), Netherlands (3.8 %), Thailand (3.1 %), Spain (2 %), South Korea (1.9 %), France (1.6 %), Iran (1.5 %), Indonesia (1.3 %), and Germany (1.2 %). Data and graphic obtained from www.trase.earth/explore (Trase 2019).

This expansion of land used for soy production has not been without consequences. According to the deforestation monitoring data of the Brazilian government, in 2015, 1.8 million ha of the area of soy in the Amazon and 3.5 million ha in the Cerrado were areas under native vegetation in 2000 (Trase 2018, PRODES 2019).

In order to address the drivers of deforestation, supply-chain information is necessary to trace the link between product demand, suppliers, their agricultural practices, and associated LUC. The Trase data is based on Spatially Explicit Information on Production to Consumption Systems (SEI-PCS), an enhanced form of material flow analysis (Trace 2019). These data support all actors of the supply chain to strengthen supply chain accountability and to transition to a more sustainable provision of agricultural commodities. The data link the import countries directly to the major traders and exporters in tropical countries and deforestation risk associated to their production activities.

The Trase 2018's yearbook shows that soy expansion in Brazil has caused both dLUC and iLUC (Trase 2018). Direct land conversion occurs when soy plantations appear short time after deforestation. A conservative estimate based on soy maps show that approximately 3% of the total area currently dedicated to soy production has been converted from native vegetation between 2005 and 2016. Indirect conversions are more complex to estimate, especially at a local level, and currently the Trase data do not allow a clear estimate. Yet, indirect conversion seems to occur more rapidly when high-value flex crops, such as soy, push the price of land up, driving land speculation and incentivising further land clearance (Trase 2018). Establishing the indirect link between deforestation and a specific crop production in a determined region is challenging, although future Trase yearbooks may seek an assessment of indirect LUC based on the indirect land conversion and crop expansion in previous years. What the data from the LAPIG alert system and PRODES (2019) show now is that very often newly converted land is first turned into pasture and later to soy production. Consequently, pasture moves progressively close to the frontiers (Trase 2018). In other words, this has caused a land "leakage", or “spill-over” effect, i.e. an indirect consequence of efforts to avoid the deforestation of the Amazon for soy production as shown in Figure 3.5 (Trase 2018). In 2006, companies responsible for more than 90% of the soy trade in Brazil committed not to purchase soy from newly cleared land in the Amazon (Soy Moratorium[3]). However, this has shifted soy expansion and deforestation patterns from the Amazon to the Cerrado in Mato Grosso state and in the Matopiba region (Figure 3.5; Gibbs et al. 2015), the world fastest growing soy frontier in the last decade (Trase 2018).

Figure 3.5 shows only direct LUC, in particular the areas with high/low deforestation and expansion in Brazil. In the figure, high direct soy deforestation is defined as at least 20% of land cultivated with soy directly converted from forestland. High soy expansion is defined as >1% growth in the proportion of the municipality that is planted with soy each year (not necessarily achieved with direct conversion of forest land). The conservative estimate based on LAPIG alert system shows that between 2005 and 2016, 850,000 ha of Cerrado vegetation in Matopiba were converted directly to soy, an area equivalent to 20% of the soy expansion area in this period (Trase 2019). Matopiba’s Cerrado provided 76% of the entire Cerrado cleared directly for soy expansion in this period (Figure 3.5). Although the figure only shows the dLUC, it also shows that the soy moratorium may have decreased soy cultivation in the Amazon region, but it has increased the soy cultivation in the Cerrado region, both at the expenses of natural vegetation (direct deforestation) and other crops (soy expansion).

In other words, this example shows that the net environmental effect of the Soy Moratorium could be quantified by the difference in impact between deforestation in the Amazon region and deforestation in the Cerrado region. Otherwise, evidences should be provided to demonstrate that, while avoiding Amazon deforestation, there have been simultaneous effort to provide at least part of the additional production capacity required either by increasing the productivity of existing soy cultivation or by expanding soy cultivation in abandoned (i.e. disused) agricultural land.

[3] The Soy Moratorium was signed by members of ABIOVE (Brazilian Vegetable Oil Industry Association) and ANEC (National Association of Cereal Exporters), which control 92 percent of soybean production in Brazil. The moratorium is a voluntary agreement designed to ensure that traders do not buy soy grown in the Amazon on land deforested after 2006.

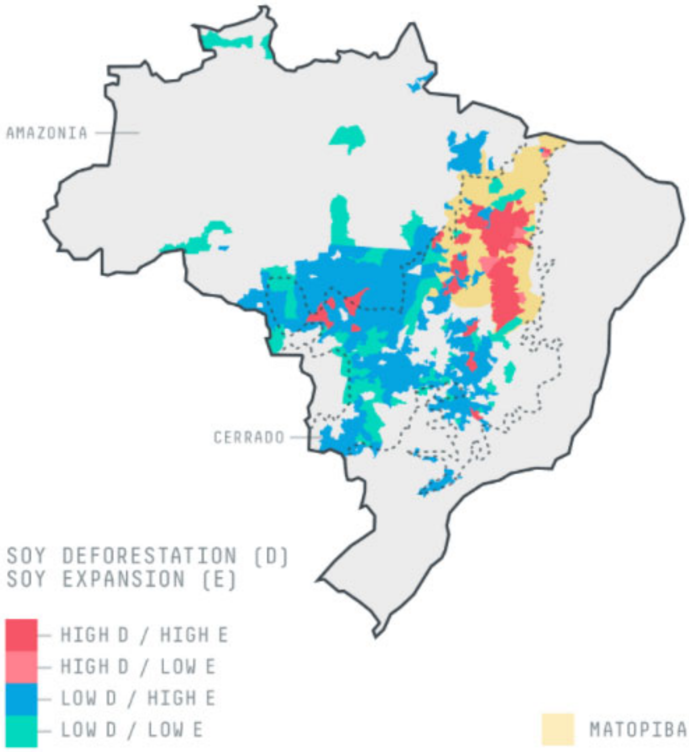


Figure 3.5 Frontiers of soy expansion in the period 2010-2016. Data and figure from Trase (2019 www.trase.earth). The four colour categories indicate high soy expansion with high direct soy deforestation ("High D / High E", in dark red); low soy expansion with high direct soy deforestation ("High D / Low E", in light red); low direct deforestation with high expansion ("Low D / High E", in blue); low direct soy deforestation with low soy expansion with ("Low D / Low E", in light green). The Matopiba's Cerrado region is shown in yellow.

Lesson learned:

- LUC model must account for iLUC to avoid burden shifting and misleading conclusions
- The net benefit of nature conservation activities shall be accounted including their iLUC effect
- Nature conservation activities should be coupled with efforts to provide additional production capacity such as:
    - efforts to intensify existing agricultural production
    - incentives to occupy abandoned agricultural land that is not deemed as land allocated for reforestation or nature restoration projects

4 Key recommendations to reduce or avoid deforestation

This section provides key recommendations to assess claims of "deforestation-free" commodities (section 4.1) and the success of sustainable land use investments supporting land development aiming at reducing deforestation (section 4.2). The recommendations are based on the review of the LUC models described in section 2 and the lesson learned by the iLUC cases examined in section 3.

Recommendations for land-based initiatives were issued by the 2019 World Resources Report by the World Resources Institute (WRI 2019). The WRI recommendations provides a broad range of land-based solutions to stabilise the climate while promoting economic development (WRI 2019). The Word Resource Institute utilised the bio-physical model GlobAgri-WRR, described in section 2.2, to quantify global food production and consumption and estimate GHG emissions from agriculture globally. Among these generic recommendations are ecosystem protection and other measures to reduce GHG emissions of bio-based materials, coupled with efforts to reduce the pressure on global land resources. The recommendations address global, economy-wide challenges in dealing with trade-offs such as increasing the food production to feed a growing population while reducing GHG emissions and preserving ecosystems (WRI 2019):

- Increase the productivity of natural resources: Increasing crop yields, milk and meat output per ha of pasture.
- Slowing the land demand: Reducing the food loss and waste, shifting diets towards plant-based foods, avoid further expansion of biofuels and support voluntary fertility reduction in countries with high fertility rates.
- Link agricultural intensification with natural ecosystem protection: Avoid that increasing productivity becomes an incentive for further land expansion by boosting legal measures to protect ecosystems and forest land from conversion to agriculture.
- Reforest land and rewet drained peatland: Drained peatland occupies around 0.5 of the global agricultural land but represents a cost-effective climate change mitigation option, as does reforestation, especially in marginal low-yielding land. These options are only achievable by reducing the projected growth of land demand and by increasing the yields of current agricultural production.
- Improve land management practices: Reduce GHG emissions from enteric fermentations by ruminants, from manure, and from fertiliser.

These recommendations show that reducing the pressure on land resources globally is crucial (WRI 2019). The first recommendation points out to the need to increase land productivity (yields) to obtain more output from a unit of land, while the third links intensification to the need of protecting natural ecosystems. The iLUC case in section 3.3 confirms these conclusions. The recommendations provided below are complementary to the WRI recommendations and focus more specifically on how specific land development deals can be assessed to verify the potential benefits they might achieve.

4.1 Criteria for net deforestation-free commodities

Claims of net-deforestation free commodities can be validated in two cases: By proving that the land occupied is outside the general market for productive land, e.g., that it is degraded and abandoned agricultural land, or by proving that the project offsets both dLUC and iLUC deforestation by setting aside a sufficient amount of land for conservation or restoration.

Offsetting deforestation requires that the indirect land use change caused by the commodity under study is first identified. The iLUC can be minimised by achieving high yields of crop output per unit of area. The remaining iLUC effect needs to be compensated by an equal amount of net delayed denaturalisation. The iLUC effect can be calculated by accounting for the accelerated denaturalisation using the 2.-0 LCA iLUC model (section 2.2). The implementation of this model in EXIOBASE (Schmidt and De Rosa 2018) shows for example that the occupation of 1 ha*year of arable land causes an average of 0.47 ha*year of accelerated deforestation through iLUC, while the remaining 0.53 ha*year is supplied by land intensification. In order to offset the GHG emissions caused by this iLUC (or leakage) effect, 0.47 ha*year of delayed deforestation needs to be additionally avoided.

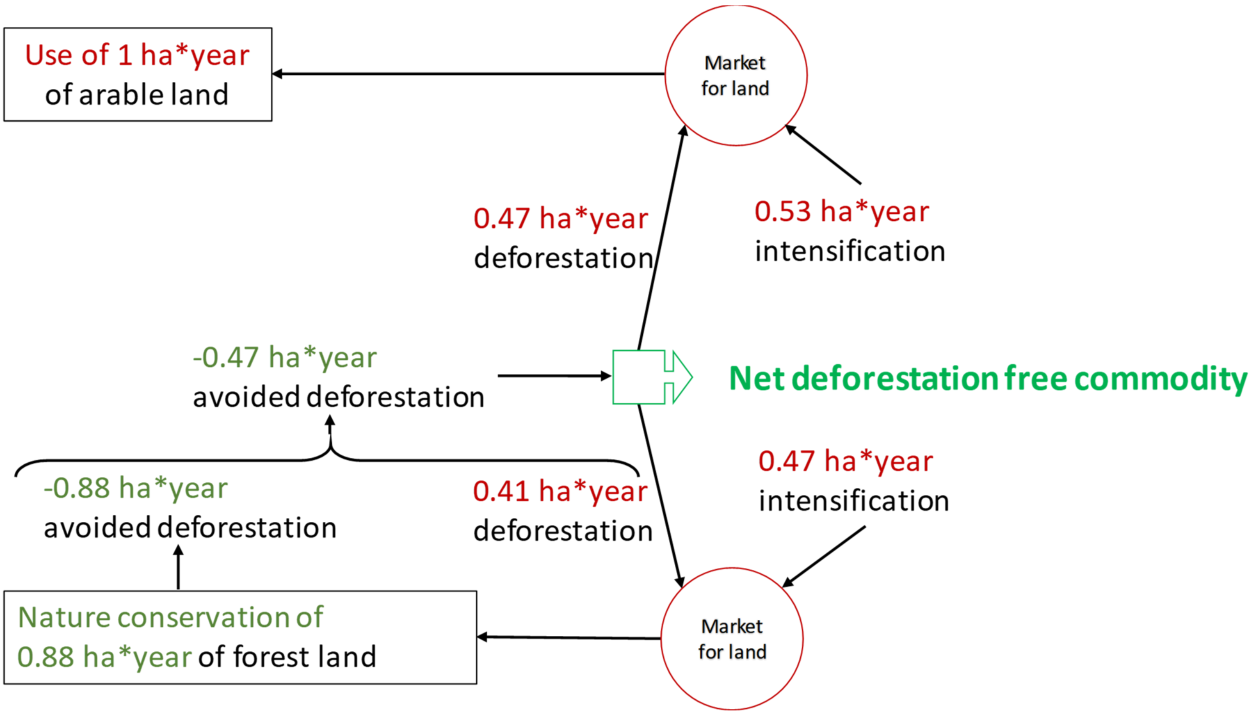


Figure 4.1 Simplified example of land use setting to claim deforestation-free commodity. The numbers are expressed in hectare-equivalent of land occupied every year (ha*year-eq.). This means that the actual land occupation is converted in ha*year-eq. taking into account the land's potential net primary production (NPP_0) of the specific region compared to the average global NPP_0.

To claim that a commodity is "deforestation-free", an amount of forest land should be set-aside in order to obtain a net avoided deforestation equal to the share of deforestation caused by the iLUC (**Figure 4.1**). When occupying 1 ha* year of land, the 0.47 ha * year of deforested land caused by iLUC should be offset by a net avoided deforestation (negative value in **Figure 4.1**) of -0.47 ha * year, obtained by setting aside -0.88 ha * year. The 0.88 ha land occupation for nature conservation also implies an iLUC effect of 0.41 ha * year, resulting in a net avoided deforestation of the necessary -0.47 ha *year. This is valid when the nature conservation area is in the same region as the land use used for producing the "deforestation-free" commodities, i.e. when the potential productivity of the occupied land for commodity production is the same as for the nature conservation area. In other cases, the land should be converted in ha*year-equivalent by using the Productivity Weights (Appendix 3) to allow comparison. In **Figure 4.1,** both the original occupation and the area for compensating nature conservation lead to land intensification of 0.53 ha*year-eq. intensification per unit of ha*year-eq., summing to 0.53 + 0.47 = 1 ha*year-eq. of intensification, i.e. showing that the full biomass production capacity of 1 ha*year-eq. land is now provided exclusively by intensification, and the product therefore can be said to be deforestation-free.

In terms of GHG emissions, the occupation of land in a specific region cause an amount of GHG emissions equal to the Productivity Weight (PW) multiplied by iLUC GHG emissions caused by the use of 1 ha*year-eq. global average arable land, $iLUC_{global}$:

Equation 2

$$GHG_{iLUC} = \text{Area occupation} * PW_{country} * iLUC_{global}$$

where,

Area occupation: The occupied area in units of ha*year.
PW: Productivity weight, see Appendix 3.
$iLUC_{global}$: GHG emissions related to the occupation of 1 ha*year global average arable land. In Schmidt and De Rosa (2018), this is 1.27 t CO_2-eq./ha-eq.*year.

For the example, the iLUC GHG emissions relating to the occupation of 1 ha*year in Brazil can be calculated as:

Equation 3

$$GHG_{iLUC} = 1\ \text{ha*year} * 1.51\ \frac{\text{ha} * \text{year} - \text{eq.}}{\text{ha} * \text{year}} * 1.27\ \frac{\text{t CO2eq}}{\text{ha eq.} * \text{year}} = 1.92\ \frac{\text{t CO2eq}}{\text{ha} * \text{year}}$$

If the land use activity foresees GHG offsetting, the amount of GHG impact saved by the land set-aside for nature conservation can be calculated as the difference in carbon stocks between the nature conservation and the arable land, i.e. the net saving, converted in CO_2-eq., multiplied by a factor 0.0072 t CO_2-eq./ha*year accounting for climate effect of the delayed deforestation per year of avoided deforestation; to this negative (avoided GHG) amount, the GHG emissions of the land occupation for nature conservation shall be added, i.e. GHG emission calculated in Equation 2 above:

Equation 4

$$GHG_{offset} = \text{Area occupation}_{nature} * (-0.0072*44/12*(C_{nature} - C_{arable}) + PW * iLUC_{global})$$

where,

GHG_{offset}: GHG emissions caused by nature conservation (t CO_2-eq.). A negative value refers to a reduction in GHG emissions.
Area $\text{occupation}_{nature}$: is the area of the nature conservation in units of ha*year.
C_{nature} is the carbon stock of the nature conservation in t C/ha.
C_{arable} is the carbon stock of arable land in t C/ha. A value of 5 t/ha can be used as default (IPCC 2006).

A negative result in Equation 4 means that the nature conservation has a net offsetting effect, i.e. the avoided dLUC GHGs are larger than the induced iLUC GHG emissions. Equations 3 and 4 show that the parameters that can be affected to achieve the largest benefit to offset the emissions from commodity production are increasing the area set-aside for nature conservation and selecting conservation land with high conservation value, expressed as carbon stock.

Key recommendations:

- Claims of “zero-deforestation” commodity can be made if the dLUC and iLUC of the amount of land set-aside for nature conservation offsets the dLUC and iLUC GHG emissions of the production activity.
- The GHG offset can be maximised by selecting conservation land with high carbon stock relative to the average carbon stock of the region where the activity takes place.

4.2 Criteria for reducing deforestation with sustainable land use investments

Sustainable land use investments aiming at avoiding deforestation could provide incentives to land developments that do not affect the frontier between nature and agriculture. This can be achieved when upgrading degraded abandoned land or by making infertile land (barren land) fertile, e.g. via desalination or irrigation facilities. More generally, sustainable land investment aiming at reducing deforestation should target existing arable land, supporting the achievement of the highest possible crop outputs per unit of area in order to reduce the global land demand.

When the land intensification aims at increasing the yield of a crop or of a different crop than the previously existing crop, the GHG emission reduction of the land intensification activity shall be measured as follows:

Equation 5

$$GHG_{intensification} = GHG_{iLUC} * \text{Area occupation}_{crop} * \left(\frac{\text{Yield before (old crop)}}{\text{Yield nat. aver. (old crop)}} - \frac{\text{Yield after (new crop)}}{\text{Yield nat. aver. (new crop)}}\right)$$

where:

$GHG_{intensification}$: the GHG emission reduction (if negative value) achieved through intensification (t CO_2-eq.)
GHG_{iLUC}: the iLUC GHG emissions per ha*year for the intensified area, as defined in Equation 2
Area occupation_{crop}: crop area affected by the intensification activity (ha*year)
Yield after (new crop): the yield after intensification of the new crop
Yield nat. aver. (new crop): the national average yield of the new crop
Yield before (old crop): the yield before intensification of the old crop
Yield nat. aver. (old crop): the national average yield of the old crop

If the sustainable land use investment includes setting aside land to reduce deforestation, the actual GHG emission reduction achieved shall be quantified including the iLUC effect of nature conservation as discussed in section 4.1. This is important to verify that the GHG emissions avoided by nature conservation are higher than the GHG emissions resulting from iLUC, i.e. that the net effect is an emission reduction compared to the baseline.

Key recommendations:

- When possible, investments should provide incentives to land developments that do not affect the frontier between nature and agriculture, by targeting degraded abandoned agricultural land, land that is left outside the general market for productive land.
- Investment shall aim at increasing the yields of existing productive land by supporting land intensification and production optimization, in order to reduce the amount of land required to obtain the same amount of product.
- The actual benefit achieved by setting-aside land for nature conservation should be calculated, since the net effect may be a negative rather than a positive environmental benefit if the land set-aside has a lower carbon stock than the land affected by iLUC.

4.3 Basic criteria for the identification of abandoned agricultural land

Agricultural land abandonment is a phenomenon that has been especially observed in Eastern and Southern Europe. In Eastern Europe, e.g. in countries such as Russia, Belarus and the Baltic countries, agricultural land has been abandoned during the transition from state-controlled to market-driven economies, due to radical changes in underlying macro-economic drivers such as national policies (Prishchepov et al. 2016). Agricultural land abandonment has also been observed in Southern Europe (Zakkak et al. 2015), where the progressive abandonment of agricultural and pastoral activities has been one of the main drivers of LUC in Mediterranean Europe (Ricotta et al. 2012). In general, land abandonment can follow drastic shocks such as economic and political transformations, natural disasters, conflicts, and similar events that deeply alter decisions on land use (Bauman et al. 2014; Prishchepov et al. 2016).

Abandoned areas are often lands of low quality (i.e. low production capacity), thus of scarce interest for crop production. Soil-crop sustainability analyses can be used to screen agronomic potential of land using GIS, in order to identify abandoned land potentially suitable for agriculture (e.g. Kukk et al. 2009). Zakkak et al. (2015) defined a forest encroachment gradient to formalize the level of abandoned agricultural land in terms of woody vegetation cover of the former agricultural area. The forest encroachment gradient identifies four forest encroachment classes based on the percentage of woody vegetation cover: 1) 0-5%, 2) 25-50% 3) 50-75% and 4) 75-100% of woody vegetation cover. If detailed data and GIS analyses are not available, the following general criteria can be considered to identify abandoned land. The criteria also intend to ensure that the site identified does not include recently cleared forest or recently and therefore only temporarily abandoned areas:

- The most recent previous land use on the area shall be agricultural land use
- The identified site shall include more than a threshold value of abandoned arable land (e.g. 50%), excluding the area covered by water bodies, settlements and roads
- Forested area that have been recently cleared shall not be considered abandoned agricultural land
- The sites shall be undisturbed from natural catastrophes such as fires
- The sites shall not be part of nature conservation or restoration projects

5 Conclusions

This report intends to support the work of the Land Use Financing Unit and the Life Cycle Initiative of the UNEP by identifying suitable LUC models to quantify the direct and indirect LUC GHG emissions of commodity productions. LUC model are necessary to identify trade-offs between land uses and inform on how land-use policies may reduce the deforestation embedded in commodity supply-chains. "Deforestation-free" commodities implies that no deforestation is embedded, directly and indirectly, in products' supply-chain or that any deforestation has been completely offset. Claims of a "deforestation-free" commodity therefore necessarily implies the quantification of commodity's iLUC. To provide this information, the report answers the following research questions:

1. **What type of LUC model is more suitable and applicable to support claims of "deforestation free" supply chain or commodities?**

Several LUC models exist with different scopes, strengths and weaknesses (section 2). In order to avoid burden-shifting and thus misleading conclusions, models accounting for LUC impacts shall always include both dLUC and iLUC. For the purpose of this study, causal-descriptive models that are adequately complex to capture the iLUC dynamics but sufficiently simple to be applied in a straight-forward manner are recommended. The 2.-0 LCA iLUC model is suggested for this purpose (section 2.4).

The model allows commodity-based LUC assessment, it is applicable to any crop type, and it is location-agnostic (section 3.1). The model provides results that can be directly used as inventory data for product Life Cycle Assessments. However, the model can also provide LUC factors that can be used to calculate the potential net LUC effect of any planned land use activity (section 4).

2. **Which criteria should be applied by investors concerned with achieving a net deforestation reduction through protection of natural land (e.g. forest protection in land use concessions) and avoidance of indirect Land-Use Change?**

Deforestation is reduced by reducing the overall pressure on land. This means that investment in land use should aim at increasing the land productivity. Investment shall aim at increasing the yields of existing productive land by supporting land intensification, in order to reduce the amount of land required to obtain the same amount of product.

When possible, investments should provide incentives to land developments that do not affect the frontier between nature and agriculture, by targeting degraded abandoned agricultural land, land that is left outside the general market for productive land.

Deforestation can also be reduced by activities aiming at avoiding the conversion of natural forested land. However, a commodity is "deforestation-free" only if the amount of land set-aside for nature conservation completely offsets the GHG emissions of the production activity. The GHG offset shall be calculated including the iLUC of both the crop cultivation and the iLUC effect of the land set-aside for conservation activity. Removing land from the market through set-aside for nature conservation will indirectly affect other areas that must supply the land production capacity displaced (**Figure 4.1**). It is therefore crucial to verify the potential net GHG effect of the LUC implied.

The GHG offset by nature conservation can be maximised by conserving forest land with high carbon stock relative to the average forest carbon stock of the region where the activity takes place (section 4).

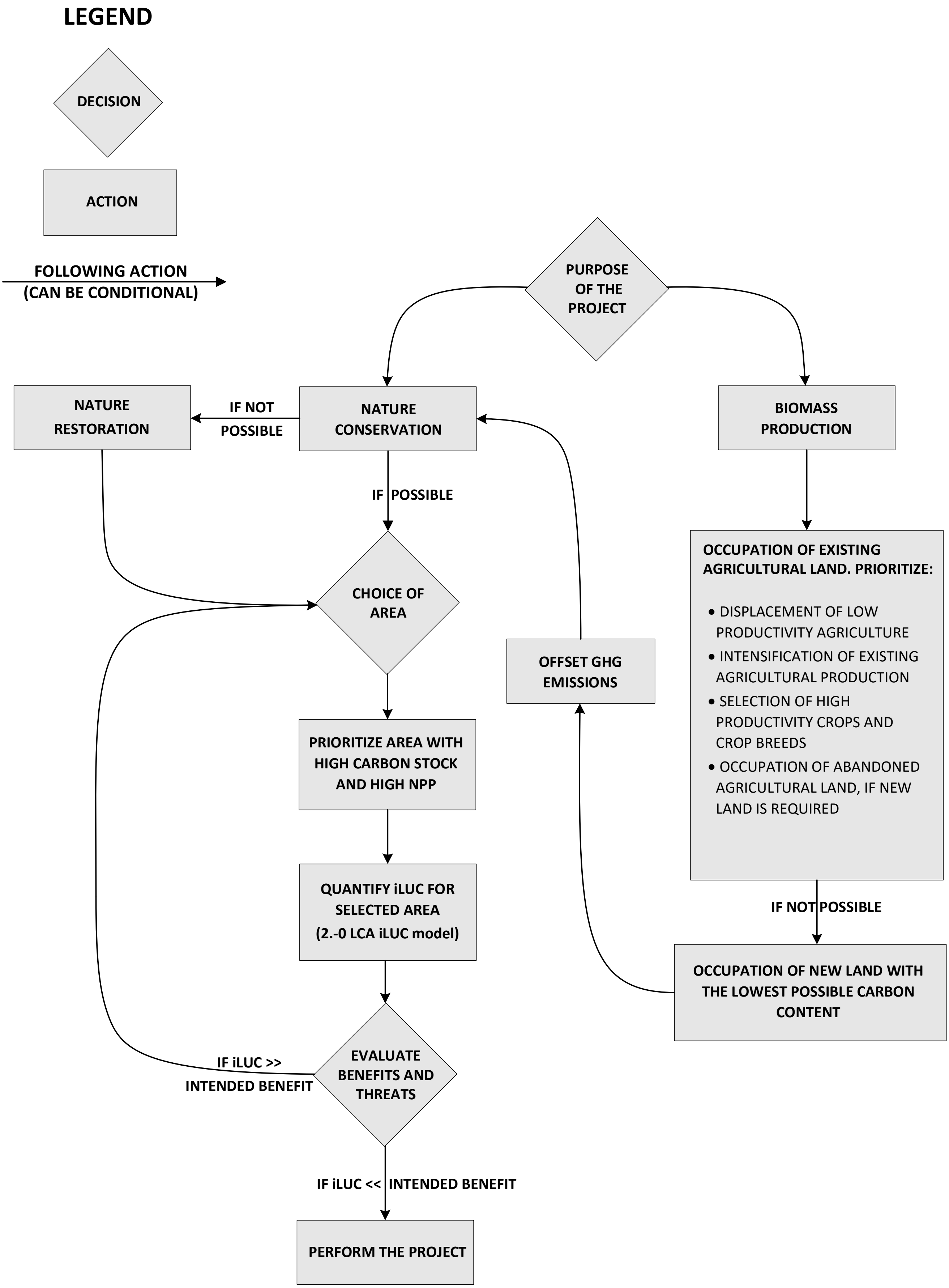


Figure 5.1 Decision tree summarizing the recommendation for sustainable land use project.

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Appendix 1: iLUC model evaluation references

Appendix Table 1 The table provide references supporting the models' assessment reported in **Table 2.13**.

	Economic Equilibrium Models (EEM)							Causal descriptive models (CDM)				Normative models (NM)		
Criterion	CAPRI	FAPRI-MU	FASOM	GLOBIOM	GTAP-AEZ	IMPACT	MAgPIE	2.-0 LCA iLUC	GlobAgri-WRR	IMAGE	Bauen et al (2010)	Quantis LUC model	PAS 2050	GHG emission protocol
Applicability and Transparency														
The model can be operated by other than the developing institute	[6]	[10]	[11] p 8	[13]	[15]	[18]	[20], [21]	[3]	[25] p 496	[4]	[26] p 13	[27]	[28]	[29]
The model is publicly available	[6]	[10]	[11] p 8	[13]	[15]	[19]	[21], [22]	[3]	[25] p 496	[4]	[26]	[27]	[28]	[29]
The model is freely available	[6]	[10]	[11] p 8	[13]	[16]	[19]	[21]	[23]	[25] p 496	[4]	[26]	[27]	[28]	[29]
The documentation is accessible and it allows to reproduce the model	[6]	[10]	[11] p 8	[13], [14]	[15]	[17]	[21], [22]	[3]	[25] p 486	[5]	[26]	[27]	[28]	[29]
The model applies to all kinds of demand for land (all crops, forest products, other land uses)	[6]	?	[12] p 2-36 (53)	[14] p 12	[15] p 5	[17] p 2	[20]	[3]	[25] p 490	[5] p 136	[26] p 13	[27]	[28]	[29]
The model has a global geographical coverage	[7] p 1274; [8] p 453	?	[12] p 1-2 (12)	[14] p 5	[15]	[17] p 2	[20]	[3]	[25] p 489	[5] p 9	[26] p 26	[27]	[28]	[29]
Methodology														
The model captures the cause-effect link between the land demand and dLUC and iLUC	[6] p 1274; [7] p 453	?	[12] p 2-36 (53)	[14] p 29	[15] p 5, [15] p 21	[17] p 5	[22]	[3]	[25] p 490, 493	[5] p 117, 137	[26]	[27] p 33	[28]	[29]
The model avoids amortization to allocate LUC emissions over time	[2] p 45	[2] p 45	n.a.	[1] p viii	[2] p 45	[2] p 45	[2] p 45	[3]	[2] p 45*	n.a.	[26] p 26	[27] p 38	[28]	[29]
The model includes deforestation and intensification to provide land production capacity	[6] p 1274; [7] p 453	?	[12] p 3-7 (61)	[14] p 29	[15] p 4	[17] p 16	[22]	[3]	[25] p 490, 493	[5] p 115, 139	[26] p 27	[27] p 11, 43	[28]	[29]
The model assumes full elasticity between land demand and supply	[6] p 165	?	[12] p 6-7 (119)	[14] p 22	[15] p7,8	[17] 21-26	[2] p 32	[3]	?		[26] p 69-70	?	[28]	[29]
The model is linked to an economy-wide model (such as input-output or EEM)	[6]	?	[12] p 1-2 (12)	[14] p 5	[15] p 5	[17] p 1	[20]	[24]	[25] p 39	[5] p 39	[26] p 6, 8,	[27]	[28]	[29]
The model distinguishes between land-use types based on land productivity or similar	[6] p 160; [9]	?	[12] p 2-25 (42)	[14] p 29	[15] p 5	[17] p 11	[22]	[3]	[25] p 493	[5] p 42	[26] p 23	[27]	[28]	[29]

*GlobAgri-WRR applies the iLUC model develop by the JRC for iLUC GHG emissions calculations.

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Appendix 2: Area potentially affected by REDD+ vs total area affected by deforestation in Brazil

A challenge in quantifying the potential LUC effect of forest conservation actions is also the relatively small area affected by the action in comparison with the total LUC involving forest land cover changes worldwide. In march 2019, Brazil received the first results-based pay-outs from the UN' Green Climate Fund (GCF). GFC accepted Brazil's REDD+ action proposal by paying for reducing the country's deforestation rates in 2014 and 2015 compared to the 1996-2010 average (GCF 2019). Brazil received a total of $96.5 million dollars for 18.8 million tons of CO_2 eq. avoided (GCF 2019). Expressed in dollars per avoided GHG emissions, Brazil received 5$ per ton of CO_2 eq. avoided GHG emissions due to REDD+ actions. However, how does this translate in terms of hectare of land preserved? How many hectares of land have the REDD+ actions actually preserved or restored? Currently, soy is the single largest most profitable export commodity in Brazil (World Bank 2019). Therefore, it is reasonable to assume that one of the main drivers for deforestation in Brazil is soybean production. Conversion of native forest (in mixed Amazon and Cerrado biome) to soybean plantations results in approximately 478 tons CO_2 eq./ha (130.5 tons C/ha including soil carbon) according to Bonini et al. (2018). This is a conservative estimate compared to the difference between native vegetation in tropical forest and deforested land of 165 tons C/ha reported by the (IPCC 2006). Thus, based on the figures reported by Bonini et al. (2018) for Brazil, receiving 5$ per ton of avoided CO_2 eq., avoiding conversion to soybean would harvest 2,390 $/ha. This provides an indicative estimation of the gross compensation received by Brazil for the REDD+ actions, i.e. excluding the costs of the action (establishing national forest reference levels, implementation of the national forest monitoring systems, providing and submitting documentation etc.). This may appear as a competitive price when compared with an estimated average gross income from soybean in Brazil of approximately 1,100 $/ha (average net profit 230$/ha according to Langemeier 2016). Nevertheless, it must be taken into account that the revenue from soybean production is annual, while the revenue from REDD+ action is tied to the country demonstrating a continuously decreasing deforestation rate compared to the initial forest reference scenario.

The difference between native vegetation in tropical forest and deforested land, estimated by the IPCC as 165 tons C/ha (IPCC 2006), is equal to 605 ton CO_2/ha. Dividing the 18.8 million tons of avoided CO_2 (GCF 2019) by 605 tones CO_2/ha, thus assuming an even larger CO_2 saving then the estimated values by Bonini et al. (2008)), the land required to achieve the financial compensation of REDD+ action, should be approximately 0.031 M ha of native land preserved (0.039 M ha assuming Bonini et al. (2008) values). This is still a very small area when compared with the total primary forest loss during the last 18 years in Brazil (23.2 M ha, **Table 1.1**) and the annual changes in deforestation rates during the same period (see Brazil in **Figure 1.2**).

Appendix 3: Productivity weights

Appendix Table 2. Productivity weights (PW) for arable land, forest land and rangeland for all countries in the world. These factors describe the potential productivity of a certain land use type in a country relative to the global average potential productivity of that type of land use.

Country/region	Arable	Forest	Grassland
GLOBAL	1.00	1.00	1.00
Austria	1.14	0.86	1.37
Australia	0.90	0.91	1.19
Belgium	1.11	0.82	1.57
Bulgaria	0.95	0.75	1.39
Brazil	1.51	1.25	2.27
Canada	0.99	0.70	0.58
Switzerland	1.14	0.77	1.23
China	0.94	0.81	0.84
Cyprus	0.72	0.57	1.05
Czech Republic	1.10	0.84	1.62
Germany	1.08	0.82	1.52
Denmark	1.08	0.81	1.58
Estonia	1.02	0.76	1.43
Spain	0.94	0.77	1.35
Finland	0.93	0.69	1.17
France	1.16	0.85	1.59
United Kingdom	1.01	0.66	1.34
Greece	0.79	0.59	1.13
Hungary	1.07	0.83	1.56
Indonesia	1.97	1.53	2.85
Ireland	1.09	0.78	1.52
India	0.91	0.90	1.37
Italy	0.98	0.73	1.28
Japan	1.04	0.79	1.48
South Korea	1.10	0.84	1.60
Lithuania	1.08	0.81	1.57
Luxembourg	1.12	0.84	1.60
Latvia	1.06	0.79	1.53
Malta	0.72	0.54	1.05
Mexico	1.08	0.96	0.98
Netherlands	1.05	0.77	1.49
Norway	1.04	0.69	1.08
Poland	1.12	0.84	1.63
Portugal	0.98	0.77	1.45
Romania	0.91	0.77	1.14
Russia	0.93	0.66	0.91
Sweden	1.08	0.71	0.96
Slovenia	1.21	0.92	1.74
Slovakia	1.13	0.88	1.71
Turkey	0.79	0.68	1.06
Taiwan	1.47	1.01	2.24
United States	1.02	0.74	0.96
South Africa	0.94	0.90	1.45
RoW Asia and Pacific	0.90	1.21	0.76
RoW Europe	1.00	0.82	1.07
RoW Africa	1.10	1.22	1.23
RoW America	1.35	1.29	1.72
RoW Middle East	0.52	0.63	0.67