IMPLEMENTATION OF LAND USE IN AN ENERGY SYSTEM MODEL TO STUDY THE LONG-TERM IMPACTS OF BIOENERGY IN BRAZIL AND ITS SENSITIVITY TO THE CHOICE OF AGRICULTURAL GREENHOUSE GAS EMISSION FACTORS

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To my son Francisco,
hoping he will be able to experience a planet
environmentally similar to and socially better than the one
I had the pleasure of knowing in my youth.

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IMPLEMENTAÇÃO DO USO DO SOLO EM UM MODELO DE SISTEMA ENERGÉTICO PARA ESTUDAR IMPACTOS DE LONGO PRAZO DA BIOENERGIA NO BRASIL E SUA SENSIBILIDADE À ESCOLHA DOS FATORES DE EMISSÃO DE GASES DE EFEITO ESTUFA DA AGRICULTURA

Alexandre de Carvalho Köberle

Março/2018

Orientadores: Roberto Schaeffer
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Programa: Planejamento Energético

O Brasil é apontado como uma importante fonte global de energia de baixo carbono, principalmente através de bioenergia com captura e armazenamento de carbono (BECCS). Contudo, existem potenciais *trade-offs* significativos entre a mitigação de gases de efeito estufa e outros objetivos de desenvolvimento sustentável, incluindo aumento no desmatamento e perdas na biodiversidade ou qualidade da água. Ademais, maiores emissões de gases não-CO_2, especialmente metano e óxido nitroso, podem reduzir o potencial da bioenergia de mitigar emissões, já que estes gases são em grande parte associados à agricultura e ao uso do solo. A bioenergia representa o elo entre a agricultura e o uso do solo por um lado, e os sistemas energéticos por outro. Até hoje, poucos estudos avaliaram de maneira integrada as interligações entre estes setores no Brasil, bem como os impactos no potencial da bioenergia oriundo das emissões de gases não-CO_2 gerados na sua produção. Esta tese apresenta um arcabouço de modelagem para explorar essas interligações, conectando diretamente a agricultura, o uso do solo e os sistemas energéticos em uma única plataforma de modelagem. Ela então explora cenários de contribuição brasileira para esforções globais de mitigação climática, ressaltando impactos intersetoriais. Avalia também de modo inovador como escolha de fatores de emissão de N_2O afetam as soluções do modelo.

Abstract of Thesis presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Doctor of Science (D.Sc.)

IMPLEMENTATION OF LAND USE IN AN ENERGY SYSTEM MODEL TO STUDY THE LONG-TERM IMPACTS OF BIOENERGY IN BRAZIL AND ITS SENSITIVITY TO THE CHOICE OF AGRICULTURAL GREENHOUSE GAS EMISSION FACTORS

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Brazil has been identified as an important global source of low-carbon energy supply, especially through bioenergy with carbon capture and storage (BECCS). However, concerns of significant trade-offs between climate change mitigation and other sustainable development goals include increased deforestation, and losses of biodiversity and water quality. Moreover, higher emissions of non-CO_2 gases, especially methane and nitrous oxide, may reduce the emissions mitigation potential of bioenergy production, since emission of these gases is mostly associated with agriculture and land use. Bioenergy production provides the link between land use and agriculture on the one hand and energy systems on the other. To date, few studies have assessed in an integrated manner the interlinkages in Brazil between these sectors, as well as the impacts on mitigation potential of bioenergy from non-CO_2 gas emissions resulting from its production. This thesis presents a modelling framework to explore these interlinkages by hard-linking agriculture, land use and energy systems in a single modelling platform. It then explores scenarios for Brazil's contribution towards global climate change mitigation efforts, highlighting the cross-sectoral impacts of meeting Paris Agreement goals. In addition, it assesses the role of non-CO_2 gases in Brazil's emissions profiles, including a novel analysis of how the choice of Tier 1 versus Tier 2 agricultural N_2O emission factors impacts modelled energy system solutions.

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1. Introduction

Human activity has so altered the natural balance of Earth's systems, a case is being made for the formalization of a new geological epoch: the Anthropocene (CRUTZEN, 2002; ROCKSTRÖM et al., 2009; ZALASIEWICZ et al., 2017). Of the global change processes at play, climate change is arguably the most impactful to humanity as a whole, with the Intergovernmental Panel on Climate Change (IPCC), in its 5th Assessment Report (AR5), listing a series of impacts on livelihoods and food production, species extinction and sea level rise, through changes in precipitation and average surface temperatures, duration of heat waves and extreme events such as wildfires and tropical cyclones. Food security is of particular concern given that population is projected to reach some 9 billion people by mid-century (IPCC, 2014).

In 2015, at the 21st Conference of the Parties to the UNFCCC (COP21) in Paris, parties agreed on a landmark treaty to tackle climate change: The Paris Agreement (UNFCCC, 2015). In Article 1, signatory countries agreed to mitigate carbon emissions in order to hold "*the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change*." Achieving this goal will require a drastic reduction in anthropogenic greenhouse gas (GHG) emissions (IPCC, 2014; KRIEGLER et al., 2018). In addition, and adding to the challenge, the Paris Agreement calls upon countries to submit their own targets and commitments, leading to a patchwork of non-binding commitments that may well prove ineffective without future ratcheting up of ambition (Schiermeier, 2015; UNEP, 2017a).

Another landmark aspiration of the international community is embodied in the United Nations 2030 Agenda, which includes the Sustainable Development Goals (SDGs), a set of 17 objectives encompassing 169 targets (United Nations, 2015a). These include from social objectives - eradicating poverty (SDG1) and hunger (SDG2) - to environmental objectives such as protecting biodiversity (SDGs 14 and 15), while providing universal access to modern energy forms (SDG7). Climate Action, and hence the Paris Agreement, is but one of the goals (SDG13), which implies that climate change mitigation will have to be implemented without sacrificing the other goals. For example, any emissions reductions will have to be achieved together with an increase in food production to feed an estimated 9 billion people by 2050 (United Nations, 2015b), while reducing environmental pressures threatening natural resources such as biodiversity, land and water resources.

In addition, increasing access to modern energy (SDG7) and sustained economic growth (SDG8) will require a transition to a low-carbon economy. As part of the low-carbon energy supply portfolio, most of the scenarios analyzed in the IPCC AR5 (IPCC, 2014) that achieve the objectives of the Paris Agreement include deployment of significant levels of bioenergy, including with carbon capture and storage (BECCS). In other words, decarbonizing the energy system may require large amounts of bioenergy with potential negative effects on agriculture and land use. Because bioenergy production and use span the agricultural, land use and energy sectors, to study the full effects of a transition to a low-carbon economy requires a type of assessment that integrates techno-economic systems analysis with socio-environmental dimensions.

Such integrated assessments usually rely on the use of scenarios that explore possible futures in a qualitative manner, with quantification often done through mathematical models known as integrated assessment models (IAMs). Globally, several such scenarios exist (GALLOPIN et al., 1997; NAKICENOVIC et al., 2000; RASKIN et al., 1998), sometimes classified into scenario families (VAN VUUREN et al., 2012). The latest development in global integrated scenarios for global environmental change are the Shared Socioeconomic Pathways, or SSPs (O'NEILL et al., 2017; RIAHI et al., 2017). These global integrated assessments are the result of complex multi model interdisciplinary analysis and are aimed at the global level.

The ultimate goal of the Paris Agreement (and climate negotiations in general) is to prevent dangerous human-induced climate change, and the IPCC AR5 Working Group 1 (WG1) report (IPCC, 2013) indicated that net cumulative emissions of anthropogenic CO_2 is the main driver of long-term temperature rise over historic times. Therefore, in order to curb temperature rise, cumulative emissions of CO_2 must be capped at a specific level. The remaining total emissions is what is referred to as a carbon budget. Carbon budgets represent our estimate of the total amount of cumulative carbon emissions that are consistent with limiting warming to a given temperature level (COLLINS et al., 2013; MATTHEWS et al., 2012; MATTHEWS and CALDEIRA, 2008; MEINSHAUSEN et al., 2009; ROGELJ et al., 2016).

In order to achieve its ultimate goal of preventing catastrophic climate change, the Paris Agreement will have to be successful at curbing not only CO_2, but also non-CO_2 gases, of which methane (CH_4) and nitrous oxide (N_2O) are the most abundant. Moreover, international consensus on how the global budget is allocated will need to arise from the negotiations, and this outcome remains uncertain. What is certain is that all climate drivers will have to be addressed appropriately, which implies contributions from all sectors of society across global regions. Although CO_2 and energy use emissions may dominate in developed countries, developing countries often have an emissions profile that have much higher participation of land use and agricultural sectors, resulting in a much higher share of non-CO_2 gases (IPCC, 2014). For instance, non-CO_2 gases represent 45% of total GHG emissions in Colombia, 28% in India, and 57% in Senegal (CAIT, 2018). Most of these non-CO_2 emissions come from the agriculture, forestry and land use sectors (AFOLU).

There are many pathways to achieve a level of emissions compatible with the goals of the Paris Agreement (CLARKE et al., 2014; KRIEGLER et al., 2018; ROGELJ et al., 2018; TAVONI et al., 2015)[1], and country contributions differ significantly (FRAGKOS et al., 2018; VAN SOEST et al., 2015). In fact, allocating emissions budgets to the different countries is a challenging exercise, with several existing allocation criteria delivering a different distribution of the global budget among countries (HÖHNE et al., 2014; PAN et al., 2017). Some developing countries, especially emerging economies, play an important role in how these scenarios attain their climate objectives, through sizeable contributions in various sectors from energy (China and India e.g.) to agriculture and forestry (Brazil and Indonesia e.g.) (IPCC, 2014; VAN SOEST et al., 2015). Therefore, a closer look at the contributions from the AFOLU sectors and non-CO_2 gases in developing countries, and how they interact with CO_2 and energy system emissions in these countries, is a valuable contribution to the extant literature.

In order to zoom in on details of these multi-gas cross-sector interactions, this thesis develops a methodology to assess land use change (LUC) in the context of energy system models, including non-CO_2 greenhouse gases. It does so in the context of Brazil, a middle-income country and emerging economy with an important agricultural sector and significant remnant of native vegetation with high levels of carbon stock. Brazil's emissions profile also has a significant share of non-CO_2 GHGs (MCTIC, 2016). In addition, the country features prominently when it comes to bioenergy production and use (EPE, 2016). The country has

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[1] In addition, see also https://www.climatewatchdata.org/pathways/scenarios#models-scenarios-indicators for a partial list of existing scenarios. Or the AMPERE project database (http://www.iiasa.ac.at/web/home/research/researchPrograms/Energy/AMPERE_Scenario_database.html) for scenarios resulting from participating models.

enormous bioenergy potential (CERQUEIRA-LEITE et al., 2009; LEAL et al., 2013; LORA AND ANDRADE, 2009; PORTUGAL-PEREIRA et al., 2015; RIBEIRO AND RODE, 2016; WELFLE, 2017), and this poses potential synergies and trade-offs between energy development, climate mitigation and other sustainable development objectives such as biodiversity conservation, water supply and food security. The proposed methodology will be evaluated through two distinct case studies. First the interlinkages between energy and AFOLU sectors are examined through bioenergy production and use. Second, the role of non-CO_2 GHGs is examined through the use of nitrogen fertilizer use and resulting nitrous oxide emissions, paying particular attention to the choice of emission factors for agricultural N-N_2O.

This analysis required the expansion of an existing energy system model, namely the COPPE-MSB (KÖBERLE et al., 2015; NOGUEIRA et al., 2014; ROCHEDO et al., 2015a) to include a land use and agriculture module in order to:

1. Create scenarios that concurrently look at energy and AFOLU mitigation options and confronts them directly, and
2. Understand the ramifications of agricultural intensification: yield improvements, fertilizer demand, non-CO_2 GHG emissions.

In order to do so, this thesis encompasses two main types of activities, namely:

1. Model development, in which
    a. It presents an integrated model for Brazil (BLUES, the Brazil Land Use and Energy Systems model) that includes energy system representation hard-linked to a land-use module so that optimization solutions can be derived for both sectors simultaneously;
2. Model application through scenarios analysis, whereby
    a. It explores possible interlinkages between energy and land systems, with special focus on:
        i. the impacts of bioenergy deployment, in particular in association with carbon capture and storage (BECCS), on land use, agriculture and livestock production;
        ii. competition between biofuels and electrification of transportation;
        iii. sensitivity of biofuel deployment to the choice of agricultural N_2O emission factors for crop cultivation.

Through these activities, this thesis sets out to answer the following overarching questions:

1. “What are the impacts imposed on the land use (LU) sectors from bioenergy’s contributions to climate change mitigation in Brazil?”

2. “How does the choice of agricultural N_2O emission factors affect the solution of a cost-optimization perfect-foresight model, especially as it applies to the energy sector?”

However, before moving on to the description of the methodology and the results, it is important to provide some background in the form of a literature review.

2. Context and theoretical background

First, in order to provide some contextual background, the review will explore (among other things and not necessarily in this order) the current state of global AFOLU emissions; carbon budget and non-CO_2 GHG emissions; land use change and competition between various forms of land use (biofuels vs afforestation e.g.); the issue of agricultural intensification; and current trends in Brazil today relevant for the topics at hand, placing them within the Brazilian national context. In addition, a review of the scenario and modelling literature will place the current research into a proper theoretical framework.

2.1 Global emissions from AFOLU sectors

The majority of global GHG emissions is in the form of CO_2 from fossil fuel combustion for energy production and from industrial processes (or fossil fuels and industry, FFI), while non-CO_2 GHG emissions are evenly split between FFI and agriculture, forestry and land use (AFOLU) sectors. Globally, direct GHG emissions from AFOLU accounted for about a quarter of all GHG emissions in 2010 on a CO_2eq basis using GWP100 (see below for a discussion of substitution metric) (IEA, 2018; IPCC, 2014).

Global energy related CO_2 emissions grew by 1.4% in 2011, reaching a record 31.6 GtCO_2eq (TUBIELLO et al., 2014), then remained flat at 0.9% for a few years before resuming growth in 2017, when they climbed by 1.4% to reach a historic high of 32.6 GtCO_2eq that year (IEA, 2018). That same year, energy demand grew by 2.1% with fossil fuels meeting 70% of that demand in spite of strong growth in new renewable capacity, which accounted for about a quarter of the growth in global energy demand (IEA, 2018).

By contrast, knowledge about AFOLU emissions remains poor, a fundamental gap that includes the lack of an international agency tasked with gathering data and providing annual reports on AFOLU emissions. This not only prevents an accurate estimation of total GHG emissions globally, but also hinders the identification of response strategies and mitigation in the AFOLU sectors (TUBIELLO et al., 2014). Energy related emissions suffer from 10-15% uncertainty range, while AFOLU emissions uncertainty is much higher, ranging between 10-150% (IPCC, 2006a). The FAO database[2] for the AFOLU sector gathers data from individual countries and fills gaps through IPCC Tier 1 methodology (IPCC, 2006a; TUBIELLO et al., 2014), as will be explained below.

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[2] http://faostat3.fao.org/faostat-gateway/go/to/browse/G1/*/E

In 1990-2010, AFOLU net GHG emissions grew by 8%, driven by increases in agriculture emissions from a 7,497 $MtCO_2eq$ average in the 1990s to 8,103 $MtCO_2eq$ average in the 2000s (an increase of 8%). These aggregate numbers were the combined result of an 8% increase in agricultural emissions, and by a decrease in forestry and land use (FOLU) emissions by 14% (a result of lower deforestation rates), and by a 36% decrease in removals by sinks (TUBIELLO et al., 2014).

2.1.1 The A in AFOLU: emissions from agriculture

GHG emissions from agriculture consist only of agricultural non-CO_2 GHGs, as the CO_2 emitted through agricultural practices is considered neutral as part of the annual cycle of carbon fixation and oxidation through photosynthesis (SMITH et al., 2014; TUBIELLO et al., 2014). In 2011, agricultural annual GHG emissions reached an estimated 5,335 $MtCO_2eq$, a full 9% above the decadal average 2011-2010, with emissions from non-Annex 1 countries accounting for three quarters of that total (TUBIELLO et al., 2014). These non-CO_2 emissions represent between 10-12% of global GHG emissions (IPCC, 2014).

As mentioned before, there is significant uncertainty on agricultural emissions. Because agricultural emissions depend on factors with high spatial and temporal variability (such as soil types, rainfall and fertilizer application rates e.g.), there is significant variation between databases regarding global agricultural non-CO_2 emissions. The IPCC AR5 reports on data from FAOSTAT, US EPA and EDGAR for historical non-CO_2 emissions. Although independent, these databases are mostly based on FAOSTAT activity data for global agriculture, and use IPCC Tier 1 approaches to derive emissions (IPCC, 2014).

The US EPA (2012) estimates that the agricultural sector is the largest contributor to non-CO_2 GHG emissions, accounting for about 54% of global non-CO_2 emissions in 2005. Enteric fermentation and agricultural soils account for about 70% of total non-CO_2 emissions, followed by paddy rice cultivation (9-11%), biomass burning (6-12%) and manure management (7-8%) (IPCC, 2014). The AR5 Synthesis Report (IPCC, 2014) breaks down emissions of non-CO_2 gases of these categories as follows:

- Enteric fermentation: comprised of CH_4, these have been growing at average annual growth rates of about 0.70%, with about 75% of the 1.0-1.5 GtCO2eq coming from developing countries in 2010, while in the Americas, this growth rate has been higher, about 1.1% per year (IPCC, 2014). Methane emissions from enteric fermentation accounted for about 40% of agriculture sector GHG emissions in 2001-2011 (TUBIELLO et al., 2014).

- Manure: the non-CO_2 emissions (mostly N_2O) grew between 1961 and 2010 at an average 1.1% per year for this category, which includes organic fertilizer on cropland or manure deposited on pastures, with the latter responsible for a far larger share than the former. About 80% came from developing countries, and 2/3 of the total came from grazing cattle, mostly bovine herds (IPCC, 2014). They represent about 15% of agriculture emissions worldwide in 2001-2011 (TUBIELLO et al., 2014).
- Synthetic fertilizer: these grew at an average 3.9% annually between 1961 and 2010, a 9-fold increase from 0.07 to 0.68 Gt CO_2eq/yr. At this rate, this category will surpass manure deposited on pasture in the next decade and become second only to enteric fermentation. Some 70% of these emissions come from developing countries (IPCC, 2014) (IPCC, 2014). In 2001-2011, they accounted for 13% of agriculture sector GHG emissions.
- Rice cultivation: In 2011, methane emissions from rice cultivation totaled 522 MtCO_2eq, about 10% of agricultural emissions that year (TUBIELLO et al., 2014).

2.1.2 Global forestry and land use (FOLU) emissions

Consisting mostly of CO_2 fluxes, primarily emissions from deforestation, but also including uptake (sequestration) from reforestation/regrowth, FOLU accounted for about 1/3 of anthropogenic emissions between 1750 and 2011, and 12% of emissions in 2000-2009 (SMITH et al., 2014). The role of forests as CO_2 sinks is important for AFOLU mitigation through forest protection measures. There has been a general reduction in FOLU CO_2 emissions across regions, with models indicating a peak in the 1980s. Drops in deforestation rates, most notably in Brazil, and afforestation in Asia have contributed to this decline (KEENAN et al., 2015). Brazilian CO_2 emissions dropped by about 80% between 2005 and 2010 (GofB, 2015a; MCTIC, 2016) due to reduced deforestation from the 2004 peak of 27,772 km^2 in the Amazon and 18,517 km^2 in the *Cerrado* biome (INPE, 2017).

It should be noted that there is much uncertainty surrounding FOLU emissions, mainly due to the fact that they cannot be measured directly, and must be estimated, which is done through a variety of methods yielding a range of results (SMITH et al., 2014). For example, FAO estimates its FOLU emissions through estimated changes in observed land use and estimated values for carbon stock in standing biomass (KEENAN et al., 2015; TUBIELLO et al., 2014). The issue of CO_2 removal by carbon sinks (particularly forests) has been debated in the last years (Erb et al., 2013; LE QUÉRÉ et al., 2013), and is a source of significant uncertainty even in some national inventories, for example Brazil's (GofB, 2015a).

A full treatment of FOLU emissions is beyond the scope of this thesis, and the reader is referred to the reports on AFOLU emissions by the IPCC (SMITH et al., 2014) and by FAO

(TUBIELLO et al., 2014) for further information. Necessary concepts and data will be explained and reported as needed in the methods chapter as they are introduced into the modelling framework developed here.

2.2 Background on scenario analysis and the SSPs

Assessment of future GHG emissions is a complex inter-disciplinary endeavor involving knowledge from engineering, economics, social and life sciences, and covering variables whose future development is highly uncertain. Exploring uncertain futures is the realm of what has come to be known as scenario analysis. A brief survey of the literature on scenario analysis is included next.

Scenario analysis is a tool for assessing the future, its uncertainties and opportunities, and provides a formal method for evaluating alternative strategies for management of private and public enterprises. Its roots go back to the 1940s with the emergence of strategic analysis, and has been influenced by the RAND Corporation, Stanford Research Institute, Shell, SEMA Metra Consulting Group and others (BERKHOUT AND HERTIN 2002). They have been used extensively in environmental assessments in which uncertainties play an important role in future development. Of particular note are the global assessments conducted on the global environment in the Global Environmental Outlook series[3], and the various IPCC reports on climate change such as the latest 5th Assessment Report, or AR5 (IPCC, 2014). Other much quoted reports utilizing scenarios include PBL's Roads from Rio +20 (PBL, 2012); reports from the Global Scenario Group such as the Great Transitions and Branch Points reports (GALLOPIN et al., 1997; RASKIN et al., 1998; RASKIN et al., 2002; RASKIN, 2006). Recently, a set of new scenarios for climate and development analysis have been introduced in the form of the Shared Socioeconomic Pathways (SSPs) (RIAHI et al., 2017).

Generally speaking, scenarios are broad narratives of possible futures, with storylines representing alternative future worlds based on internally consistent assumptions and emanating from past and present trends. Rather than trying to predict the future, "exploratory scenario approaches posit alternative framework conditions and attempt to represent plausible representations of the future ... seen as alternatives against which current strategies may need to be robust" (BERKHOUT AND HERTIN 2002).

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[3] http://web.unep.org/geo/

Quantification of these narratives is generally done via assessment modelling, using tools like the models described in this thesis. This quantification allows for the exploration of the development of selected parameters identified as important for the analysis at hand. In the case of energy scenarios, these may include aggregate quantities like primary energy consumption, Power generation or biofuels production, or actual individual commodities projections such as crude oil, coal and natural gas consumption. In the case of land use scenarios, forest area, cropland and pastures, as well as other land cover types, are examples of variables of interest. A prime example of the quantification of narrative scenarios is the series of quantifications of the five so-called marker SSPs scenarios (CALVIN et al., 2017; FRICKO et al., 2016; FUJIMORI et al., 2017; KRIEGLER et al., 2017; VAN VUUREN et al., 2017).

In addition to a narrative storyline (O'NEILL et al., 2017), the SSPs include a "set of quantified measures of development", which include drivers such as GDP or population growth rates. Although some reference quantification for these drivers is included in the SSPs, the quantification of the consequences of these drivers is left to the scenarios created by modellers based on the SSPs. For a given population size, for instance, there is a wide range of possible environmental impacts. Same for GDP level. Therefore, the potential outcomes of a large population or of high GDP is left for the scenarios to depict. The SSPs are meant as a common point of departure from which to create scenarios aiming to test different outcomes.

By itself, an SSP does not determine an emissions pathway. Rather, it represents a range of possible outcomes within a self-consistent storyline that will unfold during the course of the present century. The world described by each SSP could lead to more than one climate outcome depending on how some of the drivers behave individually or in combination with each other.

In general, SSP2 is seen as a continuation of current trends, a mix of fossil-fueled development with some level of environmental policy keeping impacts somewhat in check (FRICKO et al., 2016). For this reason, it is called the "Middle of the road" scenario, in contrast to SSP1 which is seen as a green growth scenario (VAN VUUREN et al., 2017), and SSPs 3 and 5, which follow more conventional development pathways, differing in the level of globalization and equity (FUJIMORI et al., 2017; KRIEGLER et al., 2017). Finally, SSP4 describes a dystopian world of “deepening inequalities” and low economic growth (CALVIN et al., 2017).

2.2.1 Global and national GHG emissions scenarios

As mentioned before, there are myriad GHG emissions scenarios in the literature, developed by groups from different countries and using different tools (CLARKE et al., 2014; KRIEGLER et al., 2018; ROGELJ et al., 2018; TAVONI et al., 2015). They have been used to assess the impacts of climate policies on both the global and national level (FRAGKOS et al., 2018; VAN SOEST et al., 2015), with particular attention being paid to the potential outcomes of the Paris Agreement (ROGELJ et al., 2018; VANDYCK et al., 2016). Scenarios assessing the ambition level of the Nationally Determined Contributions (NDCs) to the Paris Agreement conclude the level of ambition is not high enough (UNEP, 2017), implying the ratcheting up process needs to begin in the next round of NDCs. Scenarios consistent with Paris Agreement goals see significant decarbonization across all sectors of the global economy, but especially power generation and energy supply, which see significantly higher shares of renewable energy technologies (CLARKE et al., 2014; KRIEGLER et al., 2018; ROGELJ et al., 2018; TAVONI et al., 2015; VANDYCK et al., 2016).

Bioenergy use is projected to grow in most climate mitigation scenarios, with and without CCS, with significant potential impacts of land use and agriculture globally (MANDER et al., 2017; MURATORI et al., 2016). High levels of BECCS features in a large share of the Paris-consistent scenarios, even though its feasibility has been questioned (PETERS AND GEDDEN, 2017). In fact, not only the feasibility of CCS itself has been questioned (ARRANZ, 2015; NYKVIST, 2013; KRÜGER, 2017), but the high levels of bioenergy feedstocks required may compete with land for food production, raising concerns over food security (see Section 2.4).

On the other hand, from the purely techno-economic standpoint, BECCS and bioenergy in general rely on existing technologies and are candidates for scaling up (SANCHEZ AND KAMMEN, 2017). This remains controversial and the main criticism levelled at BECCS is that it may prove to be a dangerous distraction further delaying decarbonization sooner.

2.3 Carbon budgets and non-CO2 gases

As mentioned before, carbon budgets represent our estimate of the total amount of cumulative carbon emissions that are consistent with limiting warming to a given temperature level (COLLINS et al., 2013; MATTHEWS et al., 2012; MATTHEWS and CALDEIRA, 2008; MEINSHAUSEN et al., 2009; ROGELJ et al., 2016). Since the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) robustly established the near-linear relationship between cumulative carbon emissions and peak global temperature increase, the concept of budgets has increased in prominence in climate policy (COLLINS et al., 2013; KNUTTI and ROGELJ, 2015). Carbon budgets can be derived in a variety of ways. The IPCC AR5 provided estimates for the hypothetical case that CO_2 would be the only anthropogenic greenhouse gas, for a case which considers consistent contributions of non-CO_2 forcers, and estimated carbon budgets over various timescales (COLLINS et al., 2013; IPCC, 2014; ROGELJ et al., 2016). The AR5 reports carbon budgets associated with different climate stabilization targets as set by the Representative Concentration Pathways (RCPs) (VAN VUUREN et al., 2011), and these are shown in Table 2-1.

Table 2-1 – Carbon budgets associated with climate stabilization targets as set by the RCPs

Cumulative CO2 Emissions 2012 to 2100^a

Scenario	GtC		$GtCO_2$	
	Mean	Range	Mean	Range
RCP2.6	270	140 to 410	990	510 to 1505
RCP4.5	780	595 to 1005	2860	2180 to 3690
RCP6.0	1060	840 to 1250	3885	3080 to 4585
RCP8.5	1685	1415 to 1910	6180	5185 to 7005

Notes: ^{a} **1 Gigatonne of carbon = 1 GtC = 10^{15} grams of carbon. This corresponds to 3.667 $GtCO_2$.**

Source: Adapted from IPCC (2013)

Budgets that only look at warming from CO_2 are scientifically best understood but have limited value to real-world policy making because human activities also emit many other radiatively active species together with CO_2. Therefore, most policy-relevant carbon budget estimates take into account the influence of non-CO_2 forcers (IPCC, 2014; ROGELJ et al., 2016, 2015). These non-CO_2 contributions are estimated by either considering consistent evolutions of CO_2 and non-CO_2 forcers from integrated scenarios, like the RCPs (MEINSHAUSEN et al., 2011), or can be systematically varied (ROGELJ et al., 2015).

The non-CO_2 emissions in these scenarios, however, are often reported based on so-called Tier 1 default emission factors, derived through top-down methodology often fraught with uncertainties (IPCC, 2006a).

2.3.1 Non-CO2 agricultural emission factors

The IPCC Tier 1 approach for GHG emission factors, the so-called default emission factors, are recommended by the IPCC guidelines in the absence of reliable data to support the implementation of more empirically based values by crop and region (IPCC, 2006a). A Tier 1 approach uses default factors to calculate the emissions of GHGs from measured activity data such as nitrogen application rates, or livestock numbers and feed quality (IPCC, 2006b). Tier 1 approaches are recommended when there is a lack of data or very high uncertainties. The default values are the resulting average of empirical measurements as reported in the inventory guidelines from the IPCC (IPCC, 2006b, 2006c). Of particular interest to the present work, the emission factor associated with nitrogen application was found to result on average in 0.9% of applied nitrogen being emitted as N_2O-N, that is as the nitrogen atom in a N_2O molecule (IPCC, 2006c), a value usually rounded to 1%.

However, the IPCC Good Practice Guidance for Land Use, Land Use Change and Forestry handbook (the GPG-LULUCF henceforth) also states that for key categories, at least a Tier 2 approach should be attempted. The handbook defines a key category as:

> *A key category is one that is rioritized within the national inventory system because its estimate has a significant influence on a country's total inventory of greenhouse gases in terms of the absolute level, the trend, or the uncertainty in emissions and removals. Whenever the term key category is used, it includes both source and sink categories.*
>
> (IPCC, 2003, Ch 4)

As will be shown in Section 2.6, non-CO_2 gases are likely to dominate the Brazilian emissions profile in the long term. Therefore, parameters driving non-CO_2 GHG emissions should be classified as a key category, and therefore be assessed using Tier 2 or 3 methodology. The main drivers of N_2O emissions are in the agricultural sector and include nitrogen fertilizer application to cropland and animal wastes left on pastures. In the case of bioenergy feedstocks, the N_2O emissions of their agricultural production turns bioenergy from being "carbon free", to actually having a non-CO_2 GHG emission factor. Therefore, N-application rates to cropland and the associated N_2O emission factors are critical for an accurate assessment of climate change mitigation, globally and especially in Brazil given its status as an agricultural commodity and bioenergy producer.

2.4 Land use change and competition for land

Bioenergy production may be an attractive option for climate change mitigation, particularly in combination with carbon capture and storage, the so-called BECCS (KATO AND YAMAGATA, 2014). However, the impacts on agriculture and land use may outweigh the benefits from emissions reductions (EOM et al., 2015; MURATORI et al., 2016). (PLEVIN et al., 2010) report that GHG emissions from indirect land use change[4] (iLUC) in the literature range from the "*small, but not negligible, to several times greater than the life cycle emissions of gasoline*", and that iLUC estimates used for policy in California are at the lower end of the spectrum. MELILLO (2009) reports on research showing that emissions from iLUC will be significantly higher than from direct LUC. Moreover, lifecycle emissions from the combustion of biofuels are often assumed to be zero since the carbon was captured by the biomass, but CO_2 emissions do occur in the cradle-to-wheel chain, and may be non-zero, especially if non-CO_2 emissions from combustion are included (SMITH AND SEARCHINGER, 2012).

An important consequence of the rise of bioenergy in recent decades has been a progressive linking of energy and agricultural markets, which in the past have operated quite separately. Should bioenergy production reach the levels projected in the scenarios described in the previous section, the resulting massive production of energy from agricultural resources will link these markets tightly (TYNER AND TAHERIPOUR, 2008). The authors say this development "*is perhaps the most fundamentally important change to occur in agriculture in decades, ... and requires an integrated environment to study these markets and design policy alternatives to guide them toward designated goals*".

SLADE et al. (2014) note that the future global availability of biomass cannot be measured directly, but only modelled. The potential for biofuels as a viable energy source and GHG emission reductions option often derives from agricultural and crop models linked (or not) to energy system models. These complex software tools include many "*parameters which may be uncertain, debatable or assumed for mathematical ease*" (SEARCHINGER et al., 2015). Such parameters include the total area set aside for protection, as well as global population and diet scenarios, while land productivity is subject to technology scenarios, with increase yield assumptions playing a pivotal role (SLADE et al., 2014). A case in point, TAHERIPOUR et al. (2017) report significant improvements in the environmental

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[4] iLUC is the process by which bioenergy indirectly causes land use change by displacing an established crop or pasture, which then either moves onto native vegetation or displaces another crop or pasture which does.

performance of biofuels in the GTAP model from using updated data on land use intensification potentials. In a review of the sources of uncertainty in these models, PRESTELE et al. (2016) report that assumptions for cropland input parameters are better harmonized across models than those for livestock and forest, and that improving the quality and consistency of observational data used in these models could improve their performance.

As pointed out by both TILMAN et al. (2009) and by ROBERTSON et al. (2008), real-world biofuel sustainability faces a trilemma of environmental, economic and social facets, so that the increased use of biofuels may face tradeoffs such as land degradation, deforestation and higher food prices. However, the authors also indicate that this is not necessarily so in all cases, and “beneficial” or “sustainable” biofuels do exist. Production techniques such as no-till, precision agriculture, rotational diversity and use of abandoned lands can help deliver the benefits while minimizing the tradeoffs. Nonetheless, undesirable impacts of biofuel production at scale remain, and the true potential of bioenergy is uncertain. Hence, models and scenarios become central to the assessment of future bioenergy viability.

In terms of land competition, SEARCHINGER et al. (2015) report agricultural and crop model results for the USA where *“…25 to 50% of net calories…diverted to ethanol are not replaced… but instead come out of food and feed consumption*”, indicating a threat to food security from increased biofuel use. The authors indicate three possible basic responses when biofuels divert agricultural production away from food and feed, namely i) agricultural expansion into virgin land, ii) increasing yields to produce the same amount of food from less area, and iii) a drop in food consumption when the displaced food is not replaced (from a drop in demand due to higher prices e.g.). Clearly, options 1 and 3 are undesirable, and, while option 2 is the most desirable response, it may lead to greater use of fertilizer and water, increase GHG emissions, and appropriate the options to boost yields to meet rising food demands instead. Potential increases in GHG emissions is corroborated by MELILLO (2009), who nonetheless also adds that policies that “*protect forests and encourage best practices from nitrogen fertilizer use can dramatically reduce emissions associated with biofuels production.*”

The outlook for yield gains is also uncertain, and hotly debated. The current trend is for agricultural area to continue expanding to meet rising demand for agricultural crops, in spite of a sustained improvement in global aggregate yields (ALEXANDRATOS AND BRUINSMA, 2012). This is reflected in most agricultural model results. For example, within the recent SSP scenarios for land and agriculture show that, for the middle-of-the-road SSP2 scenario, considered as the pathway of continuation of current trends, total agricultural land continues to expand to the end of the century, driven by rising food demand (POPP et al., 2017). Similarly, TILMAN et al. (2011) point out that, if current trends of agricultural intensification in rich nations and agricultural land expansion in poor nations were to continue, 1 billion hectares of natural land would need to be converted by 2050. Clearly, this scenario runs counter to the realization of the 2030 Agenda goal to halt biodiversity loss as declared in SDGs 14 and 15 (VON STECHOW et al., 2016).

Avoiding further expansion of agricultural land without sacrificing food security requires sustained yield improvements through the course of the next decades (POPP et al., 2017; TILMAN et al., 2011). In a world following current socioeconomic and geopolitical trends (SSP2), meeting Paris Agreement objectives would require changes in patterns of agricultural production. In particular, model results indicate that cropland area for food and feed would decrease, as would pasture area, while land dedicated to growing energy crops would increase significantly by 2100, to some 500 million hectares, even as crops and livestock production peak in the second half of the century (POPP et al., 2017). This implies intensification of agriculture making room (sparing land) for bioenergy cultivation. This scenario, however, may have impacts on food security due to higher food prices (HAVLIK et al., 2014).

Increasing yields requires investments, and although yield gaps show potential for average yield improvements, there are challenges involved. On the one hand, The United Nations Food and Agriculture Organization (FAO) project annual yield increases for cereals on the order of 1% on average between 2010 and 2050 (ALEXANDRATOS AND BRUINSMA, 2012). On the other hand, SLADE et al. (2014) report concerns about over-optimism in yield improvement projections, pointing out that “*many of the easy gains have already been achieved*”, and that the practicality of closing yield gaps is subject to debate. While several estimates suggest global food production needs to double by 2050 to meet growing food, feed and bioenergy demand (FOLEY et al., 2013; TILMAN et al., 2011), current trends in yield improvement fall short of the 2.4% compounded annual growth rate required to reach that goal (RAY et al., 2013).

The basic assumption on which the land-sparing-through-intensification argument relies on is that, as yields increase, prices drop and the agricultural area declines. This causality chain assumes that demand does not change in response to falling prices. However, if demand is elastic, prices will not fall and instead of abandoning land, farmers will have incentive to expand production to increase their income. This is commonly referred to as the Jevons' Paradox whereby technological progress improves the efficiency with which a resource is used but demand does not drop as a result (ALCOTT, 2005).

On the other side of the debate is what is known as the Borlaug Hypothesis, named after Norman Borlaug, the so-called father of the Green Revolution, which states that i) people need to eat, ii) the amount of food available depends on cropland area and yield per hectare, and iii) yield improvements reduces the amount for total land required for food production. The hypothesis is most effective for broad areas, and for price-inelastic products, and therefore, it is more applicable at global rather than country scale (LOBELL et al., 2013).

In any case, the subject of land sparing through intensification is controversial and cannot be universally assumed. Rather, it is context-dependent. VILLORIA et al. (2014) find that, on a regional level, evidence on the links between technological progress and deforestation are much weaker than generally accepted. On a global level, they find composition effects to be important in low-yield, land-abundant regions where further land expansion seems more likely, on the one hand. On the other hand, land-sparring from technological innovation increase global supply through international trade, thus reducing pressure on natural lands. BYERLEE et al. (2014) make a distinction between technology-induced (more crop per hectare) and market-induced intensification (shifts in production patterns in response to market conditions), finding that, while the former is strongly land-saving, the latter "is often a major cause of land expansion and deforestation especially for export commodities in times of high prices." The authors further argue that technology-induced intensification by itself is unlikely to halt deforestation, requiring strong governance of natural resources in addition. This is corroborated by TILMAN et al. (2009) who indicate dramatic improvements in policy and technology are needed to realize the potential for sustainable biofuels.

2.5 Brazil: current trends

Brazil's position as an agricultural powerhouse has been consolidated in the past decade, which saw exports from that country soar in value (ALEXANDRATOS AND BRUINSMA, 2012). However, the economic gains of this expansion of agriculture has not been without adverse socioenvironmental impacts in the form of higher GHG emissions from agriculture (MCTIC, 2016), concentration of land ownership (HUNSBERGER et al., 2014) and deforestation (SOARES-FILHO et al., 2014). The following sections provide a literature review of current trends in Brazil with respect to agriculture, land use, bioenergy production, and emissions associated with all these activities.

2.6 Brazilian emissions profile

Historically, Brazil's main source of emissions were in Land Use, Land Use Change and Forestry (LULUCF), mainly driven by emissions from deforestation, particularly in the carbon-rich Amazon biome, but also in other biomes, especially the *Cerrado*. However, a persistent decoupling of agricultural production from deforestation has been observed recently, driven in large part by the intensification of agriculture and cattle ranching (LAPOLA et al., 2013; MACEDO et al., 2012), and by private actor initiatives such as the Soy Moratorium (NEPSTAD et al., 2009) that reduced pressure for expansion of the agricultural area. Because of this, deforestation has been drastically reduced since the peak in Amazon deforestation in 2004, bringing LULUCF emissions to a level comparable to other sectors of the economy. With that, Brazilian total emissions peaked in 2004 at around 3,000 Gt CO_2eq and have hovered between 1.2 and 1.5 Gt CO2eq since 2008 (MCTIC, 2016; OBSERVATORIO DO CLIMA, 2018). In 2010, Brazilian emissions were more evenly divided into LULUCF, agriculture, and energy sectors, and by 2015, agriculture and energy emissions represented about 23% and 22%, respectively, of total Brazilian emissions, as shown in Figure 2-1. This has focused attention on the role of these sectors in future mitigation efforts in the country, especially as it is hoped that deforestation will eventually reach zero, or at least net-zero in the coming decades (although this is far from certain).

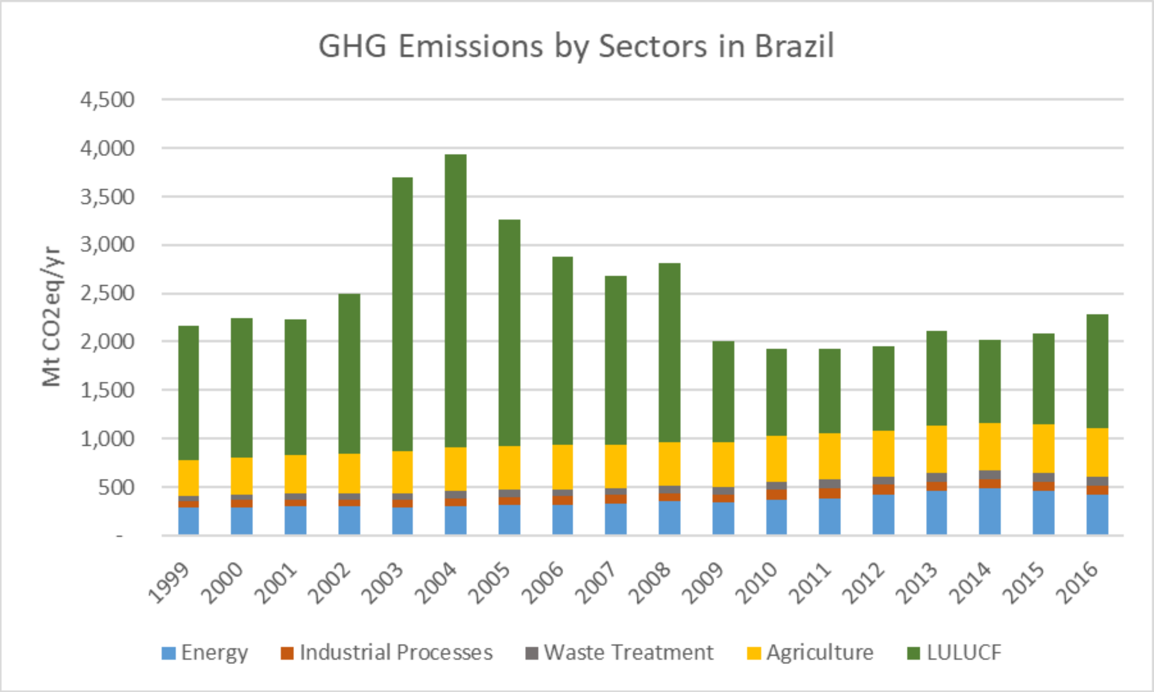

Figure 2-1 - Brazilian Emissions 1970-2014

Source: Author, based on OBSERVATORIO DO CLIMA (2018)

Given the high participation of AFOLU in Brazil's emissions, any assessment of future mitigation potential has to consider contributions from AFOLU sectors, especially in light of the fact that energy sector mitigation scenarios identify bioenergy (and BECCS) as a major contributor for mitigation efforts in Brazil (HERRERAS-MARTINEZ et al., 2015; KÖBERLE et al., 2015; LUCENA et al., 2014). Continuing deforestation to open areas for bioenergy production would negate climate targets (and the NDC), so that any significant bioenergy deployment must be weighed against other demands on land, in particular food production and biodiversity. This integrated view has become the norm of late, since the approval in the United Nations plenary of the Agenda 2030 and the Sustainable Development Goals (SDGs).

This, in fact, is corroborated in Brazil's Nationally Determined Contribution (NDC) to the UNFCCC (GofB, 2015b), which tellingly includes significant share of measures in the AFOLU sectors (Table 2-2). In addition, aspirational targets also include halting illegal deforestation, improving forest management practices, and strengthening the Low-Carbon Agriculture Plan, the so-called *Plano ABC* (MAPA, 2012). This points to the fact that a significant share of opportunities for decarbonization of the Brazilian economy lies within AFOLU sectors.

Table 2-2 - Summary of measures included in the Brazilian NDC – Source: GofB (2015b)

Sector	Target Item	Measure
Greenhouse Gases	All Sectors	Absolute targets of:
		1.3 GtCO2eq in 2025
		1.2 GtCO2eq in 2030
		(GWP-100, AR5)
LULUCF	Forestry	Strengthen Forest Code
		Zero illegal deforestation in Amazonia by 2030, with sequestrations compensating for emissions from legal suppression of vegetation.
		Enhancing sustainable forest management practices
		Restoring and reforesting 12 million hectares of forests by 2030
Energy	Primary Energy	45% renewables by 2030
		Non-hydro renewables to 28-33% by 2030
	Electricity generation	Non-hydro renewables at least 23% by 2030
		10% efficiency gains by 2030
	Transportation	Promote efficiency measures
		Improve public transport infrastructure
	Biofuels	18% biofuels in primary energy mix by 2030
	Industry	Promote new standards of clean technology
		Enhance efficiency measures and low-carbon infrastructure
Agriculture		Strengthen Low Carbon Agriculture plan (Plano ABC)
		Restore 15 million hectares of degraded pastures by 2030
		Five million hectares of integrated cropland-livestock-forestry systems by 2030

A unique feature of the Brazilian emissions profile is that the high share of emissions from AFOLU mean there is also a high share of non-CO_2 gases, in particular CH_4 and N_2O. This has been especially the case since the reduction in deforestation rates lowered CO_2 emissions from LULUCF (Figure 2-2). The share of non-CO_2 gases in the Brazilian emissions profile in 2010 exceeded 45% according to the country's *3rd Official Communication to the UNFCCC* (GofB, 2015a), the *3rd Communication* henceforth. The *3rd Communication* does not report aggregate GHG emissions but using the GWP100 metric to add up the three main gases CO_2, CH_4 and N_2O, 2010 emissions would be around 1.5 Gt CO_2eq (Figure 2-2). As recommended by the IPCC (IPCC, 2006b), official Brazilian inventories like the *3rd Communication* follow a mix of default and specific emission factors for the various processes covered, depending on whether there is enough evidence to characterize a Tier 2 or 3 emission factor or not (see

Section 2.3.1). As we shall see in Case Study 2, the choice of emission factors affects the inventories, and can skew results of IAMs.

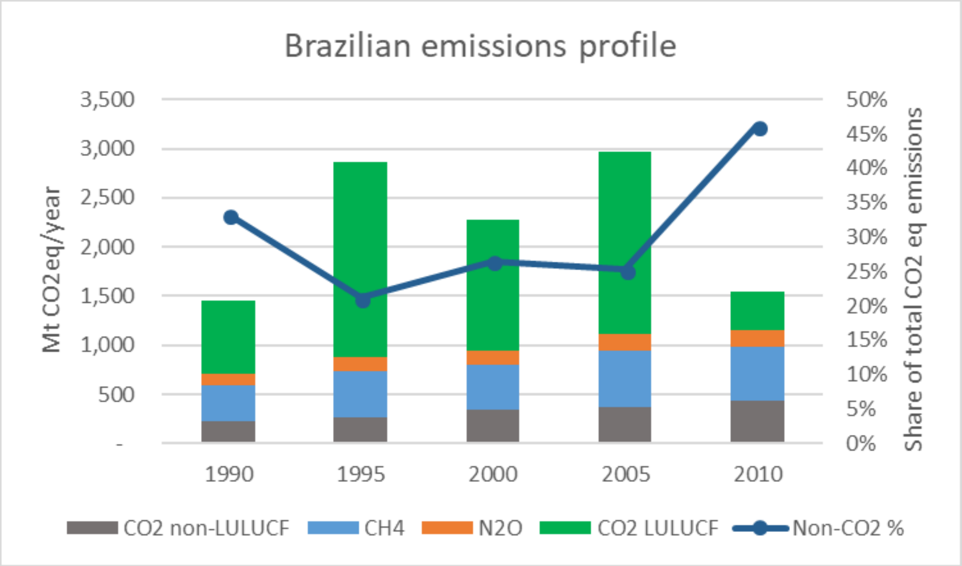

Figure 2-2 - Brazilian emissions profile using GWP100

Source: built by the author with data from GofB (2015a)

2.6.1 Existing scenarios and projections

Brazil is one of the G20 countries, and one of the top five GHG emitters in the world today. Therefore, it is not surprising that the country appears often in assessments and projections of climate change mitigation options, in spite of not being represented as a separate region in many of the most important global IAMs (the country is lumped with the rest of Latin or South America in some of the models). For example, of the main IPCC IAMs, IMAGE, AIM and GCAM have Brazil as a separate region, while MESSAGE-GLOBIOM and REMIND-MagPIE embed it in Latin America as a super-region[5]. These are the five main models involved in prominent global scenario exercises of environmental change, such as in the quantification of the SSP marker scenarios (CALVIN et al., 2017; FRICKO et al., 2017; FUJIMORI et al., 2017; KRIEGLER et al., 2017; RIAHI et al., 2017; VAN VUUREN et al., 2017). The International Energy Agency's (IEA) global energy system model TIAM[6] also lumps Brazil with Central and South America. On the other hand, the new COFFEE[7] model features Brazil as a separate region, as do EPPA[8], IMACLIM, GEM-E3, POLES and ADAGE. Some of these are computable general equilibrium (CGE) models (AIM, EPPA,

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[5] For a centralized location of model documentation, the reader is referred to the ADVANCE project wiki at http://themasites.pbl.nl/models/advance/index.php/ADVANCE_wiki

[6] TIMES Integrated Assessment Model (Loulou, 2008; Loulou and Labriet, 2008), see https://iea-etsap.org/index.php/documentation

[7] COPPE Framework for Energy and Environment (Rochedo, 2016)

[8] Emissions Prediction and Policy Analysis Model (Paltsev et al., 2005)

GEM-E3, IMACLIM), some are energy system models (MESSAGE, REMIND, TIAM, POLES), and others are land use models (ADAGE, GLOBIOM, MagPIE). Some combine to form integrated modelling frameworks allowing for the analysis of the economy, energy and land use system concurrently (IMAGE, MESSAGE-GLOBIOM, REMIND-MagPIE).

Several of these models have been involved in multi-model inter-comparison exercises that have included Brazil. The LAMP-CLIMACAP (VAN DER ZWAAN et al., 2014) exercise looked at Latin America as a whole, but in which Brazil featured prominently (CALVIN et al., 2014; KOBER et al., 2014). Global models that participated in LAMP-CLIMACAP include GCAM, EPPA, TIAM-World and ADAGE. Results showed that, although Brazil has a relatively low-carbon energy system today, as the available hydropower potential saturates, coal-fired Rankine cycle plants become the marginal lowest-cost power plant post 2030 under no climate policy scenarios. When faced with a price on carbon emissions, coal is replaced by renewables (especially onshore wind) and biomass with and without carbon capture and storage, with sugarcane featuring as the main bioenergy feedstock (LUCENA et al., 2014).

As for AFOLU sectors, CALVIN et al. (2014) report results from ADAGE, EPPA, GCAM and TIAM-World, revealing differences in future GHG emissions from AFOLU across models which are driven largely by differences in the amount of cropland expansion needed to meet agricultural demand. Models with more cropland expansion have higher land-use change CO_2 emissions. Mitigation options of the models play an important role in explaining the differences. For example, including afforestation as an option results in significant emissions reductions. Although the paper mentions links to bioenergy deployment in the model results, no explanation is offered on how these links may drive AFOLU emissions.

VAN DER ZWAAN et al. (2014) report energy system results for the LAMP-CLIMACAP project. Model results project increasing shares of low-carbon energy production, especially in the power sector. BECCS plays a large role, but no link is made to the effects this may have in the AFOLU sectors. OCTAVIANO et al. (2014) report results from the EPPA model indicating that Brazil could meet its Copenhagen and Cancun pledges to the UNFCCC largely through curbing deforestation, at a relatively small overall cost, and that the agriculture sector is responsible for the largest share of emissions. Hence, policies targeting only the energy sector will miss on a significant portion of mitigation potential in the country. GURGEL AND PALTSEV (2014) showed that land-use policies in Brazil affect the total economic cost of energy policies, indicating that interlinkages exist between the sectors.

Although Brazil is represented as a stand-alone region in some of these models, the global nature of the models implies stylized representations of Brazilian realities, which miss some important details unique to the country. For example, Brazil's diverse situations across sub-national regions means there are different costs involved for the same activity in different regions, tending to be more expensive in the less-developed North-Northeast than in the more developed Center-South region, especially for large-scale infrastructure projects (FRISCHTAK, 2016). Global models use average values for input parameters that generally overlook these differences. Therefore, the practice of concurrent use of national and global models in intercomparison exercises has been growing in the last few years[9].

Results from the aforementioned LAMP-CLIMACAP for the energy sector were corroborated by another multi-model comparison exercise (HERRERAS-MARTINEZ et al., 2015) that featured the global models IMAGE and AIM-Enduse. This exercise, as well as LAMP-CLIMACAP, featured the national model MESSAGE-Brazil (BORBA et al., 2012; LUCENA et al., 2009; NOGUEIRA et al., 2014). Results differed between the models, with IMAGE and MESSAGE-Brazil showing sustained use of biomass in the baseline, while AIM showed a decline. In climate policy scenarios, all three models projected deployment of BECCS to deliver emissions abatement.

BORBA et al. (2012) used MESSAGE-Brazil to explore how a fleet of plug-in hybrid electric vehicles (PHEV) could absorb part of the curtailed wind energy in the Northeastern region of Brazil. Another series of articles used that model to explore the vulnerability to climate change of renewable energy (LUCENA et al., 2009a), wind power generation (LUCENA et al., 2010) and potential adaptation options for hydropower (LUCENA et al., 2010). In turn, (NOGUEIRA et al., 2014) used MESSAGE-Brazil to explore the potential for coal-fired generation with CCS in Brazil.

However, MESSAGE-Brazil was limited in a few ways. First, the spatial disaggregation was limited only to the electricity system, while all other sectors were aggregated nationally. Temporal resolution was limited to seasonal variation over five time slices, which precluded a more detailed representation of load curves for power generation. In addition, energy efficiency was exogenous, meaning demand for energy services did not react to higher energy costs (LUCENA et al., 2014). Finally, the model was a purely energy system model, meaning

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[9] In addition to the LAMP-CLIMACAP project, see for example the ongoing CD-LINKS project (http://www.cd-links.org/).

land was not included at all, making it difficult to assess land demand of scenarios with high bioenergy deployment.

In order to improve the spatial, temporal and technological representation of energy supply and demand, ROCHEDO et al. (2015b) developed the COPPE-MSB model which included five geographical regions and 288 time slices. Energy demand was endogenized as were efficiency measures. An early version of this model was used to assess the Brazilian INDC (KÖBERLE et al., 2015), while another version was used to explore mitigation options for Brazil (SZKLO et al., 2017).

SZKLO et al. (2017) involved iterations between a computable general equilibrium (CGE) model, a gridded agricultural and land use model and the COPPE-MSB energy system model. Because these models were i) housed in different institutions, and ii) have very different architectures, it was difficult to study the interlinkages between them. In particular, data exchanges between land use and bioenergy were limited to one iteration of bioenergy deployment in COPPE-MSB and land use in OTIMIZAGRO. Because of the significant potential for bioenergy deployment in Brazil, such interlinkages have significant outcomes in the future of Brazilian energy, land use and climate developments. This could be achieved via a framework allowing direct linkages between sectoral models.

2.6.2 GHG mitigation potential of Brazilian agriculture

There are several studies targeting specific dimensions of the climate mitigation challenge in Brazil, or specific sectors. The AFOLU sectors have been a target of many studies, with particular interest being placed on the livestock sector and biofuel production, and on the synergies between them. To start, there has been ongoing reductions in total pasture area in Brazil through gradual intensification of livestock production (IBGE, 2007). HARFUCH et al. (2016) report a total reduction of 4.1 million hectares since 1996 but add that pressures from increasing demand for agricultural products means these pastures have been displaced by crop production.

LAPOLA et al. (2010) warn that although increased biofuels production would directly lead to only modest increases in land use emissions in Brazil, the indirect land use change (iLUC) from increasing biofuels production would push the rangeland frontier into the Amazon, where the resulting deforestation would create a carbon debt that would take 250 years to pay back. On the other hand, the authors also report that, should a modest increase occur in the stocking rate of bovine herds on Brazilian pastures, there would be enough land sparing to avoid the iLUC from biofuels. This is in line with STRASSBURG et al. (2014) who report model results indicating Brazilian pastures are operating well below their carrying capacity[10], and sustainably improving the stocking rate on the worst cases would free up enough land to meet projected demand for food and bioenergy through 2040. This is corroborated by HARFUCH et al (2016) who also report that cattle intensification is an economically viable activity even at minimum scale.

ASSAD et al. (2015) examined the potential for livestock intensification through degraded pasture recuperation and found the opportunity to sequester between 1 and 1.5 tC/ha for 10 years on some 60 million hectares of degraded pastures in Brazil. This enormous potential for intensification is evident in the Low-Carbon Agriculture Plan, or *Plano ABC* for its acronym in Portuguese (MAPA, 2012), which has 83 to 104 $MtCO_2eq$ of its total of 133.9 to 162.9 $MtCO_2eq$ (about 63%) of mitigation coming from the recuperation of degraded pastures. Another 18 to 22 $MtCO_2eq$ of mitigation are targeted to come from implementation of crop-livestock-forestry integrated systems. These systems show great potential but are off to a slow start in implementation (GASPARINI et al., 2017; GIL et al., 2015), although there are signs of a recent uptick in adoption (EMBRAPA, 2016).

Pasture degradation is defined as the “progressive loss of natural vigor, productivity and recovering capacity” demanded by the animals for adequate growth (DIAS-FILHO, 2011). More than half of Brazil´s pastures are in a state of degradation deemed advanced, and recuperation could lead to significant increase in herd productivity by reducing average age at slaughter and lifetime enteric emissions along with it, and by increasing soil carbon stocks (ASSAD et al., 2015; DIAS-FILHO, 2011). STRASSBURG et al (2014) estimate that improving productivity of Brazilian pastures could spare enough land to meet projected demands of crops and biofuels through 2040.

The Brazilian bovine herd consists of about 220 million heads of cattle on about 225 million hectares of land (IBGE, 2017a), which translates to about 1 head per hectare. A 10% improvement in the average stocking rate to 1.1 head per hectare could mean the sparing of about 20 million hectares of land. This is equivalent to about 1/3 of total planted area in Brazil today (IBGE, 2017a), and it could be used for agriculture or afforestation. ASSAD et al (2015) estimate that some 40 million heads graze on about 50 million hectares of degraded

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[10] The paper defines carrying capacity as “the stocking rate at the optimum grazing pressure ((Mott, 1960)) which is consistent with maintaining the pasture productivity”.

pastures, implying a stocking rate of less than 0.75 head per hectare. Globally, COHN et al. (2014) and HAVLIK et al. (2014) also find the intensification of livestock production could be a significant option for GHG emissions mitigation.

Degraded pasture recuperation is an endeavor that demands mechanization for activities such as soil preparation, sowing and fertilization, and it requires capital investments and improved pasture management capacity, and sometimes even supplementary irrigation (DIAS-FILHO, 2014; SMITH et al., 2007; STRASSBURG et al., 2014).

Mechanization implies higher energy demand, mainly for diesel, demanding about 10 machine-hours per hectare of recovered pasture (ANUALPEC, 2013). In addition, irrigation drives up demand for electricity (EPE, 2014), and fertilization increases N_2O emissions (SMITH et al., 2007). This means that GHG emissions from these sources increase as a result of the recuperation of degraded pastures. On the other hand, healthy pastures provide better quality forage that can reduce methane emissions from enteric fermentation (SMITH et al., 2007), while retaining more soil organic carbon (SOC) (ASSAD et al., 2015; DIAS-FILHO, 2011). Although agriculture represents just 4% of primary energy consumption in Brazil, the ongoing expansion and modernization of the sector has raised agricultural energy demand, especially diesel which is roughly 58% of the sector's energy consumption currently (EPE, 2017).

Summarizing, the intensification of agricultural practices in Brazil (especially livestock production) can mitigate AFOLU emissions on the one hand, but on the other raise GHG emissions from higher energy consumption and fertilizer use. In modelled scenarios, the balance of these mutually-cancelling outcomes is decided based on cost minimization or economic surplus maximization, depending on the model. However, several model architectures do not confront these measures directly, since they are usually represented in distinct model components, sometimes with different optimization criteria. Hard-linking energy system and land use models would allow for such a direct comparison in an integrated assessment. Recognizing that there are advantages and disadvantages to this hard linking, this thesis presents a modelling framework that does this by introducing a land use and agriculture module into an energy system model in the context of Brazil in order to examine the synergies and trade-offs embedded in GHG emissions abatement through the use of bioenergy and land-based mitigation measures. The next chapter describes the methods used to develop the new model.

3. Methods

As mentioned before, one of the aims of this thesis is to develop a set of mathematical tools that allow the examination of the interactions between the energy sector and the AFOLU sectors, namely land use and agriculture, in future climate mitigation scenarios for Brazil. Although several appropriate tools exist, they are built using very different architectures so that their interactions are not straight forward. For example, energy models that work on least-cost optimization do not easily link to land use models that seek to maximize consumer and producer surplus or allocate crops on suitability criteria; or spatial resolution of the different models do not match. In general, the driving force behind the creation of land use and agricultural models is quite different than those behind construction of energy models, so at the very least, inputs and outputs need to be harmonized in order for joint optimization to occur. This is not always trivial, and requires significant effort and time, not to mention computational power.

The focus of the present analysis is decarbonization of the energy system, and how low-carbon technology deployment at scale impacts agriculture and land use in Brazil, especially through production of bioenergy. Thus, we start with an existing energy-system model and, using its native architecture, implement a detailed representation of agriculture and land use in order to ensure a hard link between the energy and land use modules, allowing for joint optimization of the technological alternatives. Such an endeavor has been carried out before by ROCHEDO (2016), and the methods used here are similar and analogous. However, whereas that effort was done for a global model, this one is done for a national model. This imposes somewhat different constraints and requirements, but the general approach is the same. One particular difference is that, this being a national model, a higher resolution is possible, with more detailed representation of the processes that exist in the country, as well as their regional differences.

This chapter starts by describing the modelling platform used (namely the MESSAGE model builder), the existing energy system model (COPPE-MSB), and then the steps followed to introduce agriculture and land use to create the BLUES model, as well as the input data used and adopted assumptions.

3.1. The MESSAGE modelling platform

MESSAGE is a mixed integer, perfect foresight optimization model platform, designed to evaluate alternative strategies of energy supply development to meet a given demand, whether it be exogenous or endogenous. It is part of the integrated assessment models (IAMs) family and combine techno-economic and environmental variables to generate cost-optimal solutions. This solution minimizes the total cost of expansion and operation of the energy system over the entire time horizon of interest, while meeting projected energy service demands, and subject to constraints that represent real-world restrictions imposed on the variables involved[11]. The objective function of the linear programming problem is expressed below (Eq. 1).

$$\min Z = \sum_{t=1}^{k}\left[\sum_{j=1}^{m}\frac{(R_j * CE_j)_t}{(1+d)^{(k-t)}} + \sum_{i=1}^{n}\frac{(P_i * CI_i)_t + (E_i * COM_i)_t}{(1+d)^{(k-t)}}\right] \qquad (1)$$

Subject to

$$P_i^{min} \leq P^i \leq P_i^{max} \qquad (i = 1, \dots, n)$$

$$E_i^{min} \leq E^i \leq E_i^{max} \qquad (i = 1, \dots, n)$$

$$\sum_{t=1}^{k} R_{j,t} \leq R_j^{tot} \qquad (j = 1, \dots, m)$$

$$\sum_{t=1}^{n} E_{i,l,t} \leq D_{l,t} \qquad (l = 1, \dots, a)(t = 1, \dots, k)$$

$$E_i \leq P_i * FC_i \qquad (i = 1, \dots, n)$$

Where *k* is the period of analysis; *m* the quantity of available resources; *n* the total number of available technologies; *d* is the discount rate; *R* is energy extraction of resource *j* in year *k*; *CE* the unit cost of extraction of resource j in year k; *P* is installed capacity of technology *i* in year *k*; *CI* is the unit investment cost of technology *i* in year *k*; *E* is the energy produced by technology *i* in year *k*; *COM* the cost of operation and management of technology *i* in year *k*; *D* is the final demand for energy carrier *l* in year *k*; *a* the quantity of energy carriers used; and *FC* is the capacity factor of technology *i* in year *k*.

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[11] These restrictions may include, *inter alia*, resource and infrastructure availability, import options, environmental restrictions and regulations, investment limits, availability and price of fuels, and market penetration rates for new technologies.

An interesting aspect of a systems model such as MESSAGE is that it optimizes the whole energy system in question by minimizing total system cost subject to constraints, which may be different than the optimal least-cost solution for any of the individual sub-sectors (industry e.g.) making up the system. "*It is such a feature, after all, which makes MESSAGE an integrated analysis model, able to identify the indirect effects of the restrictions set forth in one sector over others*" (ROCHEDO, 2016). This is precisely what this thesis aims to examine: the indirect effects of decisions in the energy sector on the agriculture and land use sectors.

The MESSAGE framework uses two basic building blocks to represent the energy system: *commodity flows*, and *technological processes* that transform the commodities at a given cost and conversion efficiency. Representation of the technological processes (technologies henceforth) involves a set of parameters that define how the technology works and how much it costs. These parameters include capital and operation and maintenance (O&M) costs; construction times and plant lifetimes; their input and output commodities, as well as auxiliary or secondary inputs and outputs; minimum utilization factors, and activity factors tied to the activity of a technology, such as emission factors and intermittency constraints. The conversion efficiency of a given technology is subject to i) the thermodynamic efficiency of the conversion process being modelled, and ii) physical mass balances. The conversion efficiency parameter is defined by the user to reflect what is commercially available in the real world, with the option to improve over time following technological learning (JUNGINGER et al., 2010). Similarly, costs may decrease over time following a learning curve (ARROW, 1962), usually set exogenously.

3.2. Challenges in implementing land use in the MESSAGE platform

An agriculture and land use module was created using the architecture of the MESSAGE framework to represent technological processes and commodity flows such as land conversion, crop and livestock production, and processing of raw commodities into final products (e.g. wood into charcoal or solid biomass). In addition, technologies that transform energy crops such as sugarcane or woody biomass into primary bioenergy feedstocks were introduced that represent the transaction costs and capacity constraints of collecting, transporting and processing of the feedstock commodity before it can be used in the conversion process. Several decisions were made about how to best represent Brazilian agriculture and land use systems in a format compatible with the MESSAGE framework.

The MESSAGE platform was designed to suit energy systems modelling through a suite of commodities that can be transformed into each other via processes (sometimes referred to as technologies), at a certain cost and with a certain efficiency, subject to constraints (Section 2.1). The number of commodities and processes, as well as constraints, is determined by the user, who also needs to provide cost and efficiency parameters, as well as bounds (upper, lower or fixed) for the constraints. In short, the energy system is modelled as interlinked flows and stocks of commodities, and capacity and activity of processes. Process efficiency is given by the input to output ratio of the input and output commodities. Costs are implemented as capital investment costs (*capex*) and operation and maintenance costs (O&M), which can be either fixed (*fom*) or variable (*vom*) costs associated with the operation of a process. Thus, the costs of commodities are introduced into the model via the operation costs of the processes needed to generate a unit of a given commodity. In fact, a commodity has no intrinsic price or cost associated with it but is linked to the cost of producing it. For example, at the resource level, oil in the ground has no cost until it is extracted by processes with costs and efficiencies to become crude oil at the primary level, which will already have a price or cost associated with its extraction. This is analogous to the price formation of commodities in the real world.

This setup is ubiquitous in energy systems modelling and is common to the majority of cost-optimization models that constitute the energy module of most integrated assessment models (IAMs). Although suitable for modelling energy, this framework does not lend itself easily to land use modelling where land is a fixed asset that cannot be moved, and whose stock is constant (that is, land is always land and its amount is constant). Moreover, land has many uses, and how land is used can change from one time period to the next, but the sum of the areas of all the land uses in a given region must equal the total existing land at every time step of the model. This is a constraint that does not have an obvious counterpart in energy systems, so energy system models are not equipped to deal with such a variable[12]. In addition, there is a strong spatial component to land value (and thus, cost) given by soil and climate (edaphoclimatic) conditions and distance to markets. These are highly local in nature, whereas energy commodities are the same everywhere. Although wind and solar energy do

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[12] Although total system energy conservation is a law of thermodynamics, most of the energy content of energy carriers is lost as waste heat, which is not fully tracked in energy systems modelling. This energy conservation only occurs for isolated systems. Although the 1st Law of Thermodynamics imposes total energy conservation in conversion processes, this conservation is maintained even through the degradation of the quality of energy (entropy) and its ability to do work (2nd Law of Thermodynamics). This is the case for the system itself in case of isolated systems, or in the totality of system-surroundings for open systems.

have spatial variability, it is usually modelled as a non-spatial resource in energy systems modelling frameworks (GERNAAT, 2011; KÖBERLE, 2013).

Therefore, modelling land use in MESSAGE endogenously involves pushing the architecture in ways it was not meant to. The methodology follows that used by ROCHEDO (2016), in which the base year distribution of land cover types (agriculture, forests, etc) are taken as the initial state, and allowed to change in order to accommodate evolving requirements of land area to meet demand for agricultural products. The next chapter describes the methodology developed to create a land use module fitted into an energy systems model built in the MESSAGE platform.

The base year state of the land cover in Brazil is described by an initial land use map, the elaboration of which is described in Section 3.3.2. But first, we take a look at the existing energy system model which will form the basis for BLUES, namely the COPPE-MSB model.

3.3. The BLUES model

This thesis encompasses two main types of activities, namely:

1. Model development, and
2. Model application through scenarios analysis

Under activity 1, the work involved further developing an existing energy systems model by adding to it a land use and agriculture module hard-linked to the energy sectors in order to study the linkages between climate change mitigation, bioenergy deployment and land use change (LUC) in Brazil to 2050. The existing energy system model used as the starting point is the COPPE-MSB model, and it is described in the next section. The following sections then describe the actual development of the new land use and agriculture module, the methodological steps followed, and the data used and how it was implemented. Then, the next chapter applies the new model in two demonstrative case studies.

3.3.1. The COPPE-MSB energy systems model

COPPE-MSB (KÖBERLE et al., 2015; PORTUGAL-PEREIRA et al. 2016; ROCHEDO et al. 2015) is a development and expansion of the MESSAGE-Brazil model developed by the Cenergia lab at COPPE/UFRJ (BORBA et al., 2012; LUCENA et al., 2009; HERRERAS-MARTINEZ et al., 2015; LUCENA et al., 2015; NOGUEIRA et al., 2014). Techno-economic parameters that form the input deck of COPPE-MSB were derived from various sources (KÖBERLE et al., 2015; NOGUEIRA et al., 2014; PORTUGAL-PEREIRA et al., 2016; SORIA et al., 2015). Techno-economic input parameters of IAMs in general, and also of COPPE-MSB, include specific investment costs (CAPEX, in US$/kW), construction times (years), conversion efficiency (%), and any technical or economic specifications that may be required to appropriately model the performance of an energy technology (investment and O&M costs, minimum utilization time, inputs and outputs, auxiliary inputs and secondary outputs among others).

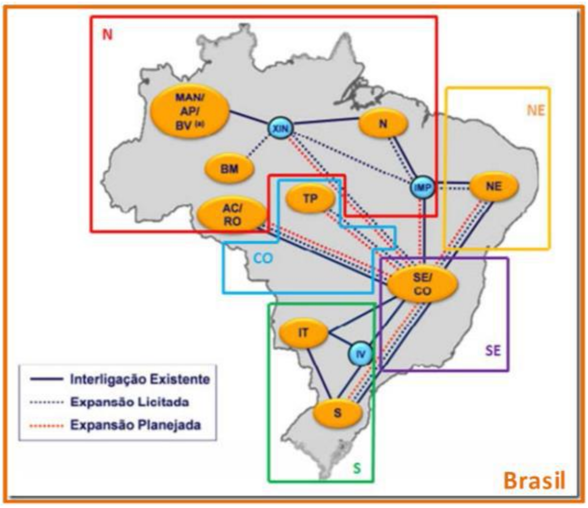

Figure 3-1 - Geographic division of Brazil in BLUES

Source: SZKLO et al (2017)

COPPE-MSB divides Brazil into five subregions (*North*, *Northeast*, *Southeast*, *South* and *Mid-West*) that are nested into a main *Brasil* region through which international imports and exports flow (Figure 3-1). Also, Brazil's industrial sector is not separated into the five subregions, but rather modelled as a national sector within the main region. The same goes for the services and the waste treatment sectors. The five subregions have their own processes portfolio and new capacity is installed into each subregion separately. The main commodities flow across subregions via bilateral import/export processes. Each subregion also has its own electricity load curve as well as hydro, wind and solar potential curves at the same resolution, namely 12 representative days (one for each month) divided into 24 representative hours. The temporal profile of intermittent sources in COPPE-MSB model is controlled by a maximum bound of 25% of the total electricity generation, a result given by operation (dispatch) models (MALAGUETA et al., 2013; MALAGUETA et al., 2014; SORIA et al., 2016; MIRANDA et al., 2017). An earlier version of COPPE-MSB was also used to support Brazil's NDC submitted in 2015 (GofB, 2015b), and to generate the energy projections in SZKLO et al. (2017).

A generic representation of a process in COPPE-MSB and a sample of the energy system structure in COPPE-MSB are shown in Figure 3-2.

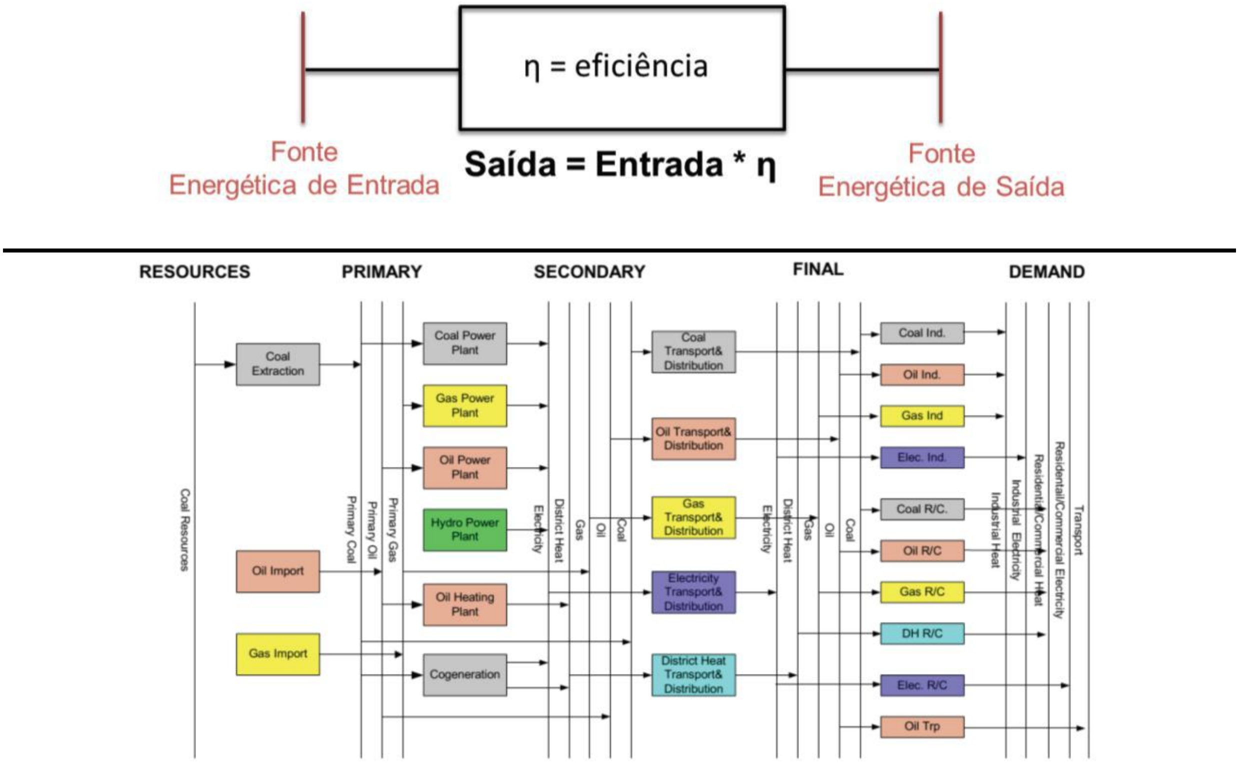

Figure 3-2 –Generic representation of a process in COPPE-MSB (top) and sample of the structure of the COPPE-MSB model

Source: SZKLO et al. (2017)

Final use in COPPE-MSB (and BLUES as well) is defined in terms of energy service. The term “energy service” here follows the definition proposed by FELL (2017): “*Energy services are those functions performed using energy which are means to obtain or facilitate desired end services or states*”. So final use is defined in terms of “lighting” and “heating” instead of “kWh of electricity” or “Mbtu of natural gas”. Therefore, units are in lumens, passenger-kilometers (pkm) or ton-kilometers (tkm). These services are provided by end use processes such as cars, airplanes, light bulbs or stoves for example, each with several options of varying costs and efficiencies that the model chooses to minimize total system cost according to the objective of the scenario it is solving. These end-use processes (technologies) take as input energy carriers at the final energy level such as gasoline, diesel, kerosene (jetfuel), electricity, natural gas, LPG, firewood, charcoal.

These final energy carriers, in turn, are products of processes that take primary and or secondary energy commodities, such as refineries, power plants and distilleries. The exception is rooftop solar photovoltaics (PV), the only technology delivering electricity directly to end users as final energy, and firewood which is also used in its primary state. Finally, primary energy commodities must be extracted from their natural state by technologies that mine a resource such as biomass, coal, crude oil, natural gas, uranium, as well as wind, solar and hydraulic power. Secondary energy denotes an intermediate level in which primary commodities have been transformed from their raw, natural state, but are not yet ready for final use, be it because it needs to undergo further transformation or to be distributed to where the end users are located.

Commodities and processes in the bioenergy chain, from primary biomass to final wood, charcoal or biofuels, are the link between the energy system and the land use and agricultural systems. First generation ethanol can be made from any sugary feedstock, and in Brazil sugarcane is the main crop. Although there is only a pilot plant making second generation ethanol in Brazil today, cost reductions and efficiency improvements are expected to make lignocellulosic ethanol an important bioenergy carrier in the future (DIAS et al., 2014). Conversely, sugarcane provides both the juice from which 1st gen ethanol is distilled as well as bagasse, which can be either burned to drive steam turbines to make bioelectricity or used as feedstock for 2nd generation ethanol production. On the other hand, high yield lignocellulosic crops such as elephant grass may compete quite well with sugarcane.

COPPE-MSB decides which technology to deploy based on final cost of the system, so that the whole production chain of the fuel is taken into account, as well as emissions in case there is an emissions price or constraint implemented into a scenario being analyzed. Hence the drive to include the complete bioenergy chain going back to the agricultural crop production of the primary feedstock. Moreover, although direct energy use by agriculture is small – less than 4% in Brazil (EPE, 2015) – inputs into crop and livestock production have high levels of embedded energy. In fact, globally some 30% of energy use and 20% of emissions can be tied to agricultural production when the whole production chain is take into account (FAO, 2011). Therefore, it is important to model energy demand explicitly in order to correctly account for ramifications of increased agricultural production on other sectors, especially the chemical industry producing fertilizers from (mostly) natural gas.

3.3.1.1. Bioenergy in COPPE-MSB

Because bioenergy use in Brazil is dominated by sugarcane products (EPE, 2016), the COPPE-MSB model represents the sugarcane chain in considerable detail. It includes explicit representations of several sub-processes that form the chain from the production of the sugarcane to the utilization of its products. These include sugarcane crushing; bagasse burning to produce steam for combined heat and power (CHP) plants; sugar, 1st and 2nd generation ethanol, and bioelectricity production, and carbon capture and storage. The parameters that form the numerical basis of these products is taken from literature as will be described next.

Production of sugarcane is modelled as an aggregated operation at a given yield and cost reflecting average Brazilian values in 2010 and evolving at a fixed rate to mimic autonomous efficiency improvements, at various stylized costs to represent a step cost-supply curve. This is precisely the process which is expanded and more accurately modelled as explained in the rest of this chapter. The 2010 base year yield is set to 74.3 t/ha and grows by an average annual rate of 3% to reach 96.7 t/ha in 2050. Up to 445 Mt can be produced at US$20/t, with additional production possible at US$30, US$45, US$60 and US$100 per ton. This agricultural production part of the model was completely replaced by the methodology explained in this chapter, so the details of the old COPPE-MSB implementation of agricultural production will not be further described. However, from the crushing of the sugarcane forward, the new model kept the COPPE-MSB structure so a description is warranted next.

Following production, the sugarcane is crushed in a process requiring 16 kWh per ton of cane as reported by ENSINAS et al. (2007), which produces sugarcane juice, bagasse and straw in a proportion of 0.4 ton of juice, 0.3 ton of bagasse and 0.3 ton of straw per ton of cane. Each of these intermediary products undergoes further processing to deliver sugar, ethanol and bioelectricity. First generation ethanol is produced from juice via fermentation and distillation to produce hydrated ethanol as described by ENSINAS et al. (2007). The stand-alone ethanol distillery process has a fixed yield of 4572 GJ of hydrated ethanol per ton of juice (11431 GJ per ton of cane). The combined sugar-ethanol facilities can operate on sugar or ethanol campaigns, at 25/75 shares of each.

Hydrated ethanol can also be produced via hydrolysis of bagasse, at a yield of 149.3 liters of hydrated ethanol per ton of bagasse as in a process described by WALTER AND ENSINAS (2010). Hydrated ethanol is then further distilled to anhydrous ethanol which can happen via two processes, namely azeotropic cyclohexane distillation or molecular sieves.

The sugarcane industry is a net producer of energy, and it powers its processes by burning bagasse in CHP plants that produce both steam and electricity, with excess electricity exported to the grid. The steam is used to power the processes within the sugar mill and/or ethanol distillery. There are two CHP options for the production of steam and electricity, one with a back-pressure turbine and one with an extraction–condensation turbine operating with condensation pressure at 0.085 bar pressure. In addition, steam can also be generated via bagasse gasification which feeds a gas turbine for electricity generation, with exhaust gases used for steam generation in a HRSG operating at 2.5 bar of pressure (ENSINAS et al., 2007).

To see a stylized structure of the sugarcane chain see Figure A-1 in the appendix. Note that the figure shows not only the ethanol production chain from COPPE-MSB, but also the land use and agriculture elements that were added to build BLUES, as described in the following sections.

In addition to ethanol, biodiesel can be produced from fatty acids via transesterification (FAME) for 1st generation biodiesel. For advanced biofuel routes, both biodiesel and biokerosene can be produced through Fischer-Tropsch or biomass-to-liquids routes (TAGOMORI, 2017). Biokerosene can also be produced via an alcohol-to-jetfuel (ATJ) route that uses ethanol as its input and produces both biokerosene along with a smaller share of biodiesel as a by-product (DE JONG et al., 2015).

3.3.1.2. CCS in COPPE-MSB

Besides low-carbon energy sources like hydro, wind, solar and nuclear power, COPPE-MSB also boasts a detailed suite of carbon capture and storage (CCS) technologies that can be deployed to achieve low-emission pathways. There are capture technologies in fossil and biomass combustion, bioliquids production and industrial processes.

CCS in fossil fuel use for energy supply has options in power generation, including in coal- and natural gas-fired power generation. Industrial processes that have CO_2-capture options include associated gas reinjection in pre-salt oil fields and select processes in transformation industries.

There are BECCS options as both post-combustion capture in bioelectricity production (from bagasse and biomass), and as process CO_2 capture in the production of biofuels (liquids) production. This includes CO_2capture in the fermentation phase of ethanol, and in biomass-to-liquids (BTL) diesel and kerosene routes, a Fischer-Tropsch synthesis route in which the CO/H_2 ratio of the syngas needs to be adjusted and the compressed CO_2 is easily extracted (TAGOMORI, 2017).

The captured carbon has to be transported and stored, with both processes explicitly modelled in COPPE-MSB, with investment costs per kilometer based on average lengths. Carbon pipelines are modelled as intra- and inter-regional, with intra-regional pipelines averaging 200 km in length and inter-regional pipelines averaging 1000 km in length. Transported CO_2 is injected into geological structures that include salt-water and freshwater aquifers and depleted oil and gas fields, the latter allowing for enhanced oil recovery (EOR) practices that make it a potentially lucrative process. Costs and capacity of CO_2 injection and storage follow (MERSCHMANN et al., 2016; NOGUEIRA et al., 2016; ROCHEDO et al., 2016).

3.3.1.3. New additions to COPPE-MSB

The BLUES model builds on the COPPE-MSB model by adding a land use and agriculture module and coupling it to the energy system model via bioenergy feedstocks such as sugarcane for ethanol and bioelectricity, soybeans and animal fats for biodiesel, and lignocellulosic material for bioelectricity, 2nd generation ethanol or biomass-to-liquids (BTL) diesel and biokerosene. In addition, a suite of advanced biofuel technologies not present in previous versions were also introduced to better represent the bioenergy chain. These include an alcohol-to-jet (ATJ) route (CARVALHO et al., 2016; DE JONG et al., 2015) implemented as an add-on unit to existing ethanol distilleries (ATJ repurpose), and the possibility to use biodiesel in bunker fuels for shipping in blends up to 20% by volume. In addition, the cost assumptions on electric vehicles have been updated to reflect recent developments (BNEF, 2017), following a cost curve that delivers cost parity with conventional vehicles by 2040. Another important biofuel production route that features prominently in the results of this study is biomass-to-liquids diesel (BTL-diesel) production with and without CCS. This is a Fischer-Tropsch synthesis route in which the CO/H_2 ratio of the syngas needs to be adjusted and the compressed CO_2 is easily extracted (TAGOMORI, 2017).

3.3.2. Land use and agriculture in BLUES

Modelling the land use sector involves two basic sets of data, namely

i) those representing the current state of land use in Brazil, and
ii) conversion processes that transform land in one state into another state.

The latter is governed mainly by dynamics in the agricultural sector involving crop and livestock production, the main drivers behind land demand, and will be described in Section 3.3.2.5. We turn now to the discussion of the former, which is comprised of maps and datasets on current land use such as agricultural zones, protected areas, urban areas, water bodies, and so on. In addition, there need to be maps and datasets that provide the amount and location of certain parameters that may be of interest to the analysis, such as above and below ground biomass of standing land use classes (forests, e.g.), soil organic carbon (SOC) content of the various soils in Brazil, distance to cities and suitability maps of different crops' growing potential. The information contained in these will be needed to determine *inter alia* the GHG emissions from deforestation, forestry residues, length of growing seasons, potential yields of various crops, and the cost of bringing goods to market.

BLUES includes land use in its modelling, and therefore can be called a land use model. However, it is not a gridded agricultural model including bio-geophysical modelling of the crops and their edaphoclimatic determinants of productivity. Rather, BLUES values of parameters for costs and productivity are exogenously defined. Moreover, a full assessment of agricultural potentials is not the point here, neither is the assessment of impacts of land policy on land-specific variables such as land tenure, for example. The main objective of the BLUES land use module is to support efforts to study the interlinkages between bioenergy use in climate mitigation scenarios and the resulting implications for land use and agriculture which, in turn, may expand or constrain choices for bioenergy technology deployment in the model. The lad use module does this by providing a portfolio of bioenergy feedstocks that are then transformed into energy carriers by conversion technologies.

Model preference for one or another bioenergy feedstock is governed by levelized cost of energy (LCOE) of the output commodities of the conversion technologies. The final cost of production of the energy carrier that is eventually used in the energy system is what determines if one feedstock is preferred over another. For example, agricultural residues may be less costly than sugarcane, but the collection of this dispersed resource coupled with the high cost of transforming it into a biofuel means that, per unit of energy delivered by the whole chain, producing biofuels from sugarcane may still be a less expensive option than using residues. Hence the importance of having a good representation of the agricultural system that prouces the feedstocks for bioenergy production. For a country like Brazil, an exporter of agricultural commodities and home to important remnants of undisturbed natural lands and biodiversity, GHG mitigation scenarios that rely too heavily on bioenergy may be solving the climate problem by creating other environmental issues. Intensification of agricultural practices is often expected to spare land for afforestation and/or bioenergy production. This is not without challenges though, and the dynamics at play were explored in Chapter 2 by way of the Borlaug Hypothesis versus Jevons' Paradox debate.

Since the ultimate goal of applying BLUES is to study energy and climate change under constraints from land use and agriculture, it makes sense that only the variables that influence those results should be included in the modelling framework. For that reason, the only agricultural commodities that need to be modelled explicitly are either those that i) serve as feedstocks for bioenergy production, or ii) have a high impact on land use and thus on prices of agricultural commodities in general. Thus, the broad range of products from Brazilian agriculture can be reduced to a few specific crops, plus a few aggregated product categories. This reduces data requirements and computational time. In addition, auxiliary variables that enable the land use transitions and production of agricultural commodities also need to be modelled. These include diesel and fertilizer use, as well as GHG emissions resulting from all the processes discussed so far.

Likewise, the types of land cover (forests, croplands etc) can also be reduced to a few representative categories. The set of land use categories should give a picture of the land use distribution at a given time. We turn now to the construction of the initial state of land use in Brazil.

3.3.2.1. Land use maps

Developing land use maps is the domain of geosciences and beyond the scope of this work. Hence, an existing initial land use map had to be identified and selected, which can fulfill the desired purposes. Until very recently, there were no publicly available land use maps for the whole of Brazil. In the last few years, a number of institutions have made available such maps developed through various geographical techniques such as remote sensing and field assessment and various modelling techniques (LANTMAN et al., 2011). The main options available today are the maps provided by CSR-UFMG[13] (SOARES-FILHO et al., 2016), by LAPIG[14], by IBGE[15] (IBGE, 2017b), and by mapBiomas[16]. At the time when the current

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[13] Centro de Sensoriamento Remoto , Universidade Federal de Minas Gerais, available at http://maps.csr.ufmg.br/

[14] Laboratório de Processamento de Imagens e Geoprocessamento, Universidade Federal de Goiás, available at https://www.lapig.iesa.ufg.br/lapig/index.php/produtos/dados-geograficos

[15] Available from https://ww2.ibge.gov.br/apps/monitoramento_cobertura_uso_terra/v1/

[16] Available from http://mapbiomas.org/

work began only the CSR-UFMG and LAPIG maps were available for download and use. For different reasons, both were included in the analysis as described in the next sections.

The most detailed of the available maps in terms of disaggregation of land cover types is the CSR-UFMG map *uso_da_terra_2013* (henceforth the CSR map) representing land use in 2013 as allocated by the land use model OTIMIZAGRO (SOARES-FILHO et al., 2016). The map represents the cultivated area of 14 crops, double-cropped areas, planted forests and pastures, plus the natural remnants of forests and savannas, both inside and outside of protected areas (SOARES-FILHO et al., 2016). It also shows urban areas and water bodies which were used here to create an exclusion mask for agricultural activities.

A separate CSR map provides information on pastures divided into categories of intensity as measured by stocking rate in units of AU per hectare[17], the CSR pasture map. LAPIG's maps also include a map of pasture areas divided into categories of intensity much like CSR maps, and as will be explained below, was chosen to constrain the intensification potential of livestock production processes.

Figure 3-3 shows the CSR map with all its original classes, not all of which are explicitly needed to perform the objectives of this thesis. Therefore, the land cover types that are not essential are aggregated through reclassification into a smaller set of land use classes that share certain basic characteristics such as vegetation type, purpose, or location. A representative set of distinct land use classes was chosen to optimize representation and minimize computational requirements in the MESSAGE framework, as described next.

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[17] AU = animal unit, defined as 450 kg of live weight per hectare.

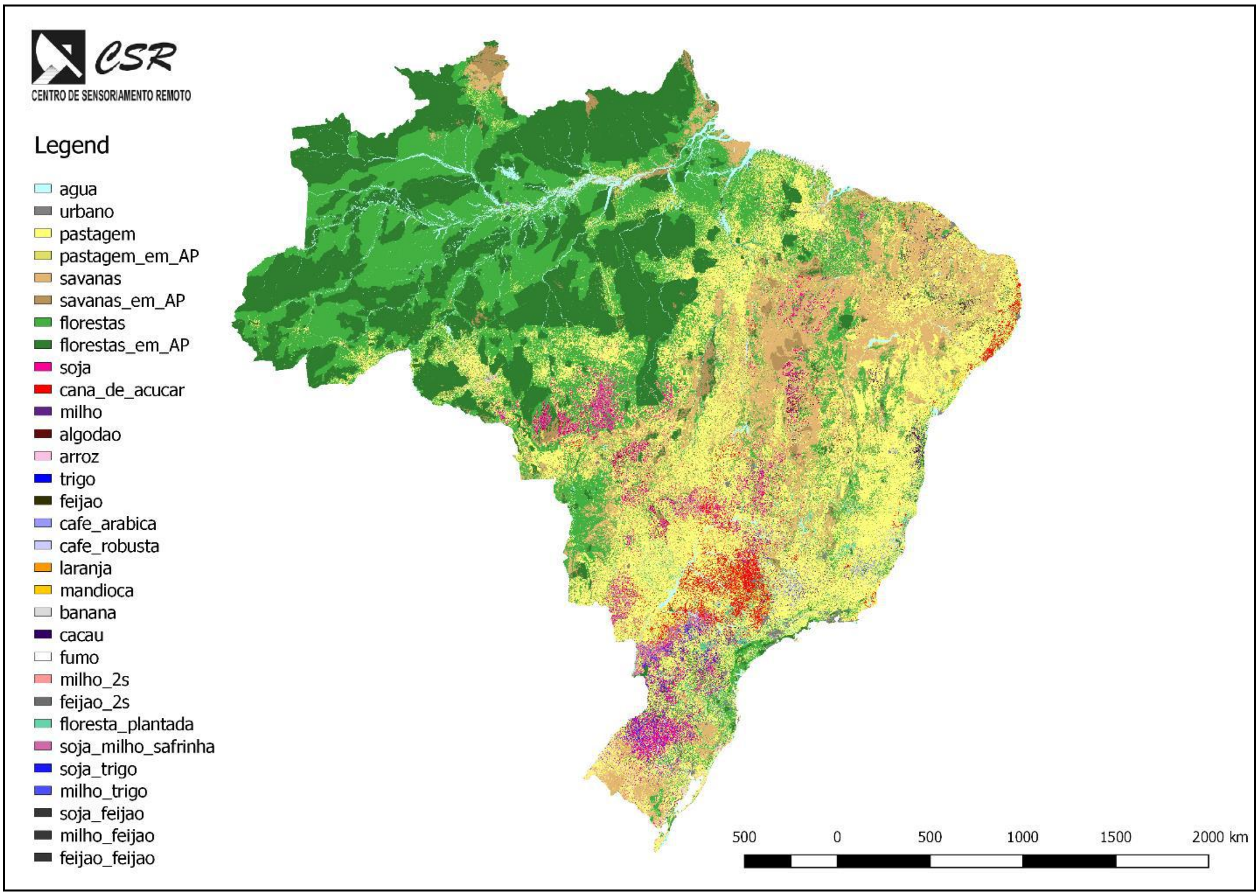

Figure 3-3 – The CSR-UFMG land use map in 2013 for Brazil

Adapted from SOARES-FILHO et al. (2016)

3.3.2.2. Aggregating CSR to BLUES land use classes

The original land use classes from the CSR map were reclassified into eight land use classes according to Table 3-1. The aggregation was done using QGIS software to reclassify the land use classes. As can be seen in the legend of Figure 3-3, there are a number of double-cropping alternatives in the original CSR map, including soybeans-wheat, soybeans-maize, maize-maize, maize-wheat as well as others involving these crops and beans. All these areas are reclassified as double-cropped, indicating the area in the base-year area supporting two annual harvest, or double-cropping, in Brazil. Urban and water areas were aggregated into no-go areas for agriculture.

Table 3-1 – Aggregation of land use classes from CSR-UFMG maps to BLUES land use classes
***PA = protected areas**

BLUES LU class	Original LU classes in CSR map
Single-cropped	Single crop areas with: soy, sugarcane, corn, cotton, rice, wheat, beans, coffee, cassava, oranges, bananas, cocoa and tobacco.
Double-cropped	Double-cropped areas with: soy/corn, soy/wheat, soy/beans, corn/beans, beans/beans
Pastures	Pasture inside and outside protected areas
Planted Forests	Forests planted for wood, paper or bioenergy
Savannas	Savannas outside protected areas
Savannas in PA*	Savannas inside protected areas
Forests	Forest outside protected areas
Forests in PA*	Forest inside protected areas

The aggregation of all crops into a single land use class is justified in that the goal is to give the model an area of land that is used for agriculture in the base year, and then allow the model to allocate that area to the various crops according to its cost-minimization criteria. This process will be explained in more detail in Section 3.3.3. First, we take a look at how pastures are represented in BLUES, and how the initial areas of the two pasture LU classes are determined.

3.3.2.3. Pasture area in the base year

There is much uncertainty around total pasture area in Brazil. For example, the CSR-UFMG pastures map (BARBOSA ALVIM et al., 2015) estimate 220 Mha of total pasture area in Brazil, while (BGE (2016) estimates 260 Mha, and LAPIG (2016) report 165 Mha. This wide range is explained by different assumptions and methodology, such as the inclusion or not of low-intensity grazing on natural pastures and public land. An examination of the CSR-UFMG maps reveals a much larger area occupied by pastures than the LAPIG maps. In fact, pastures with a stocking rate below 0.84 AU/ha in the CSR map cover a much larger area than that given by the LAPIG map under a stocking rate below 0.9 AU/ha, with significant differences in area in each region.

Given such large uncertainties and the high mitigation potential of livestock intensification in Brazil, we opted for a conservative estimate of the area with potential for intensification, currently under low intensity grazing. Thus, it was decided that the total pasture area would come from the CSR pastures map (BARBOSA ALVIM et al., 2015) in order to maintain consistency with the CSR land use map (SOARES-FILHO et al., 2016) used for the other land use classes. However, in order to constrain the potential for intensification to levels described by ASSAD et al. (2015), it was decided that the area with potential for livestock intensification from degraded pasture recuperation in each region would be given by the area of the LAPIG map (LAPIG, 2016) with a stocking rate below 0.7 AU/ha. This is exactly the chosen cutoff value for Low Capacity pastures of 0.7 AU/ha, which yields national area for Low Capacity pastures of 69.1 Mha, a number in line with ASSAD et al. (2015).

It is important to note that the classification of Low- and High-capacity pastures is somewhat arbitrary, with the cutoff value of 0.7 AU/ha being chosen in order to reflect the accepted definition of degraded pastures as those with stocking rates below 0.75 AU/ha (ASSAD et al., 2015; STRASSBURG et al., 2014). However, the term "degraded pasture" may not apply to all of what we term Low Capacity pastures. In some low productivity areas, the pastures may not support much more than the current low capacity on a sustainable, long-term basis. This may be particularly the case in the semi-arid region of northeastern Brazil known as the *caatinga*, a biome characterized by low and highly irregular precipitation, and sandy or rocky soils with low organic matter, all leading to long periods of low pasture carrying capacity (POMPEU et al., 2015).

Figure 3-4 shows subsets of the LAPIG pasture map, with the left panel showing areas with stocking rate below 0.9 AU/ha, and the right panel area with stocking rate below 0.7 AU/ha. It is easy to see how the vast majority of low capacity pastures are in the semi-arid *caatinga* biome of Northeastern Brazil.

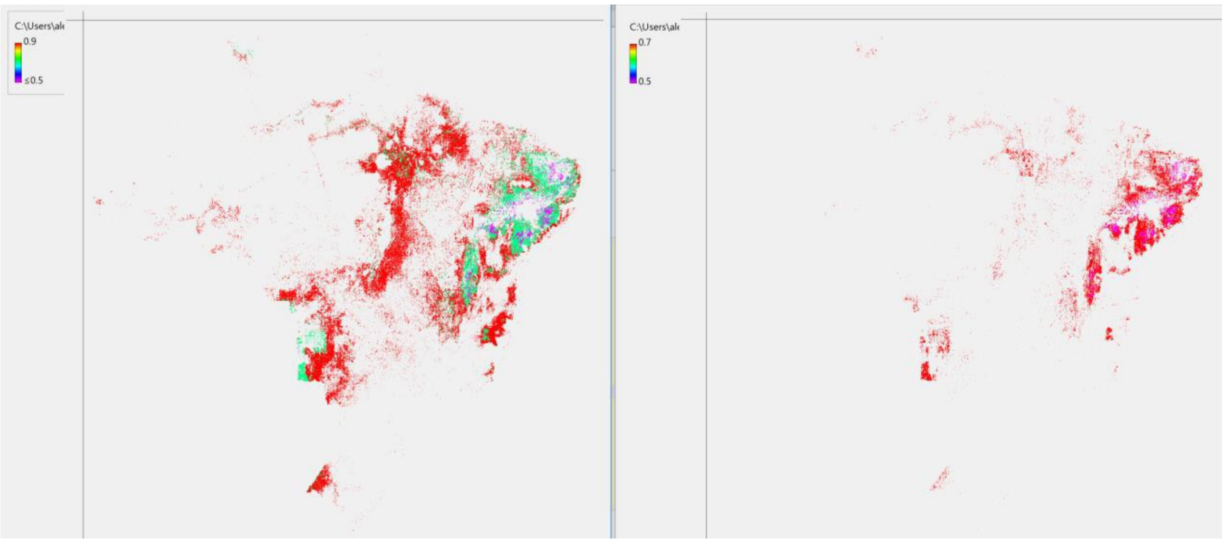

Figure 3-4 – Pasture area with <0.9 AU/ha (left) and <0.7 AU/ha (right)

Source: built by the author with data from LAPIG (2016)

The area of each pasture type in BLUES for the base year is shown in Table 3-2.

Table 3-2 – Area in the base year of the two pasture types modelled in BLUES, in each region (Unit = Mha)

Mha	NO	NE	SE	SU	CO
Low-capacity pastures	16.23	50.73	41.47	10.87	40.09
High capacity pastures	15.54	3.46	3.94	9.19	21.84
TOTAL	31.77	54.19	45.41	20.06	61.94

Source: elaborated by the author based on the CSR map (SOARES-FILHO et al., 2016)

As seen in Table 3-2, there is much more area under low-capacity pastures than under high-capacity pastures. In general, Brazilian pastures operate below their carrying capacity as demonstrated by STRASSBURG et al. (2014), so there is ample potential for intensification in all regions. Figure 3-5 shows the carrying capacity of Brazilian pastures from the LAPIG map.

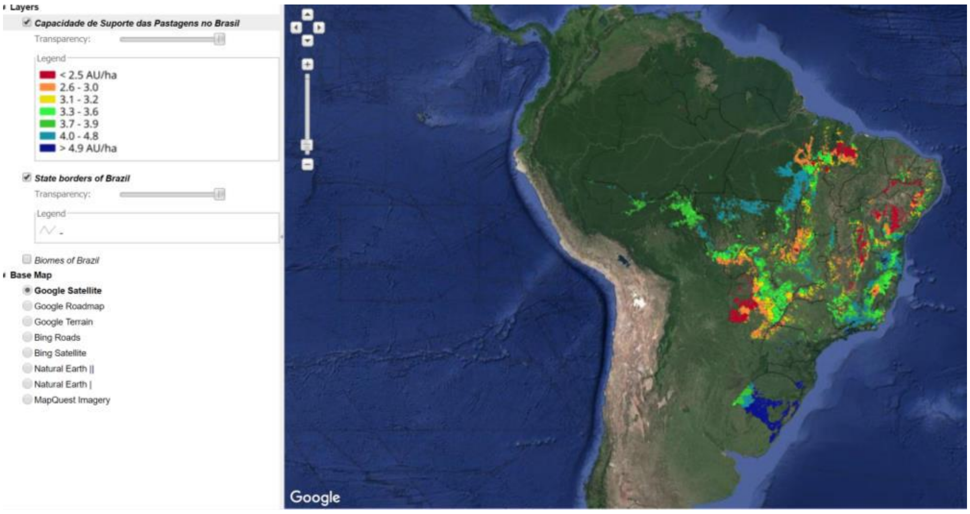

Figure 3-5 - Carrying capacity of Brazilian pastures

Source: prepared by the author based on LAPIG (2016)

3.3.2.4. *The initial land use map in BLUES*

To create the initial land use map used to calculate land areas available in BLUES, land use classes in the CSR map were aggregated according to the classes in Table 3-1, with low- and high- capacity pastures defined from an overlay of the LAPIG map on the CSR map, as described in Section 3.3.2.3. This map was used to calculate areas of each land use class in the base year, that were then implemented into BLUES as constraints. Figure 3-6 shows the resulting initial land use map.

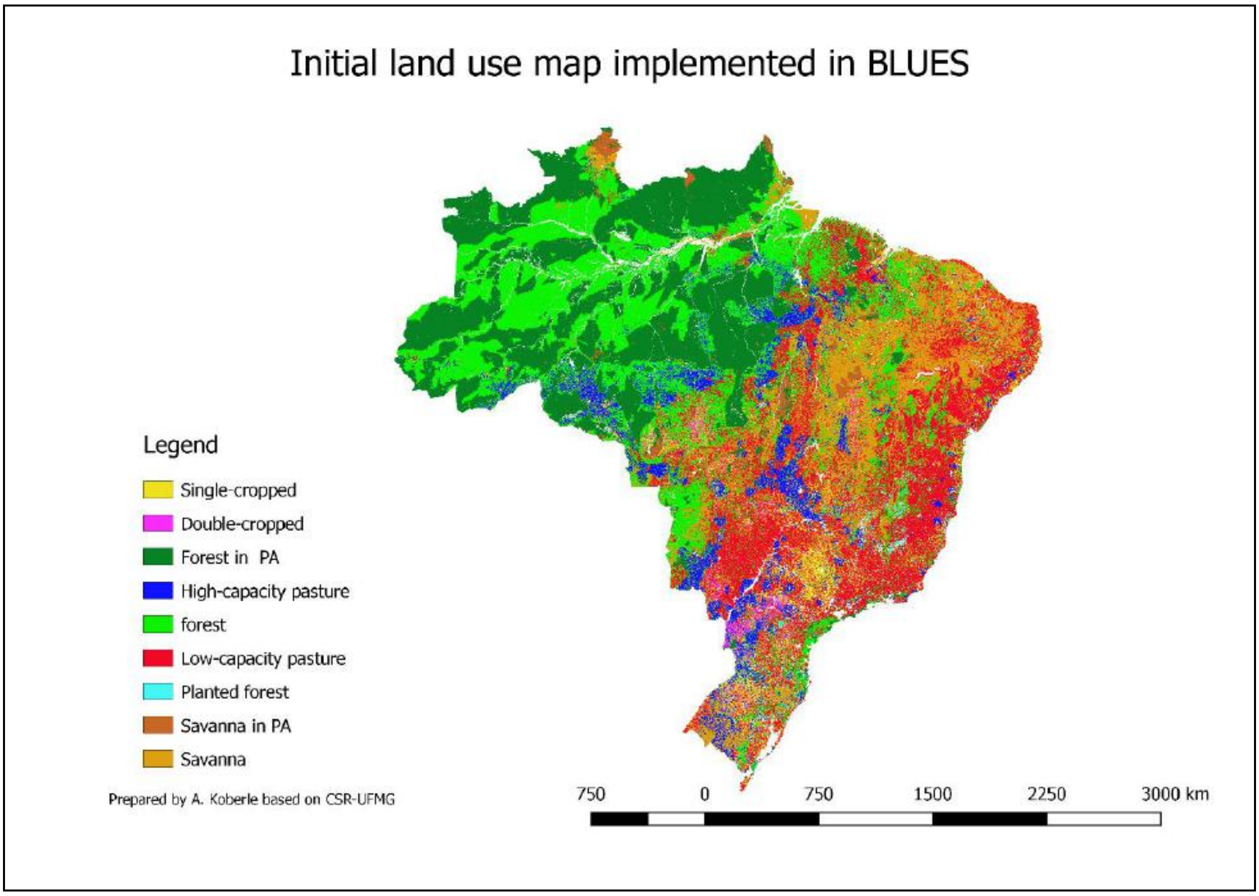

Figure 3-6 – Land use allocation map resulting from the aggregations employed (see text)

Source: built by the author with data from SOARES-FILHO et al. (2016) and LAPIG (2016)

Table 3-3 shows the resulting areas of each land cover type modelled in BLUES for the base year 2010. Total cropland area (Single Cropping, Double Cropping and Planted Forest) adds up to 56.5 Mha. Pasture areas total 213.4 Mha.

Table 3-3 – Areas of the land cover types in BLUES for the base year 2010 (in million hectares)

Land Cover Type	Area in 2010 (Mha)
Forest	210.8
Forest in PA	189.5
Savanna	110.1
Savanna in PA	12.1
Lo Cap Pasture	159.4
Hi Cap Pasture	54.0
Single Cropping	41.7
Double Cropping	8.6
Planted Forest	6.2
Integrated Systems	0.0

Source: own modelling, original results

3.3.2.4.1 Uncertainty in base year cropland area

Being derived from the CSR/UFMG maps (SOARES-FILHO et al., 2016), the land use classes are not easily compared to other data sets like IBGE[18] and MAPBIOMAS[19], because these classify land cover types differently. Because the land use classes in the different dataset overlap, it makes comparison very challenging. For example, what here is classified as *Forest* and *Forest in Protected Areas*, MAPBIOMAS classify into “Forest Formations” which also include “Savanna Formations”, while IBGE calls it “Forest Vegetation”. In turn, what here is *Savanna* and *Savanna in Protected Areas*, MAPBIOMAS classifies as a combination of “Savanna Formations” and “Grassland”, while IBGE has “Field vegetation” and “Natural Pastures”. Cropland in both IBGE and MAPBIOMAS can be either purely agricultural or a “mosaic” of agriculture-pasture and agriculture-forest. There is no way to say if one classification choice is “better” than the other. They are simply different ways to classify land use. But it makes validation challenging. In addition, as mentioned in Section 3.3.2.1, there is little agreement on areas between the three datasets mentioned here (CSR, IBGE and MAPBIOMAS).

Nonetheless, according to IBGE, the *Area Planted or Destined for Harvest*[20] was 65,374,591 hectares (IBGE, 2018), which differs by about 16% from the cropland area found by this methodology as presented in Table 3-3. As in the case of pastures (Section 3.3.2.3), there is also uncertainty around planted area of crops in Brazil. For example, a much-publicized estimate done by NASA released in 2017 indicated that cropland in Brazil occupied

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[18] https://www.ibge.gov.br/geociencias-novoportal/informacoes-ambientais/cobertura-e-uso-da-terra/10867-cobertura-e-uso-da-terra.html?=&t=cobertura-e-uso-da-terra

[19] http://mapbiomas.org/map#coverage

[20] Área Plantada ou Destinada a Colheita

63,994,479 hectares in 2017 (IBGE, 2018). In 2016, EMBRAPA Territorial had estimated that area to be 65,913,738 hectares (EMBRAPA, 2017), so these two are broadly in agreement. Since agricultural area in Brazil has been expanding (IBGE, 2018), it suggests the IBGE numbers may be overestimates. This discrepancy is evidence of the uncertainties around estimates of land use data in Brazil, that both the NASA and the EMBRAPA estimates for 2016 and 2017 are about the same size as IBGE estimates for 2010. The CSR map is developed from satellite imagery (remote sensing) and official statistical data and is therefore more in line with the NASA estimates.

3.3.2.5. Land use transitions in BLUES

With the initial land use map defined, the model will allocate land to different purposes to meet land demand by changing one type of land cover into another as needed. The permitted land use transitions in BLUES are shown in Figure 3-7. As can be seen from the figure, the low capacity pastures are at the center, with all transitions from the natural world necessarily having to go through this land cover type. Although in the real world additional transitions do occur, limiting the allowed number significantly reduces computational time. However, this is not a problem since, within each time period, more than one transition is allowed. So, in reality, a hectare of a given land cover type could be transformed into any other land cover type in a single time period, by stepping through multiple conversions. Therefore, limiting the types of transitions allowed does not necessarily mean imposing additional constraints on the model. It simply means the model has to go through the steps shown, with the costs of transitioning between land cover types being additive.

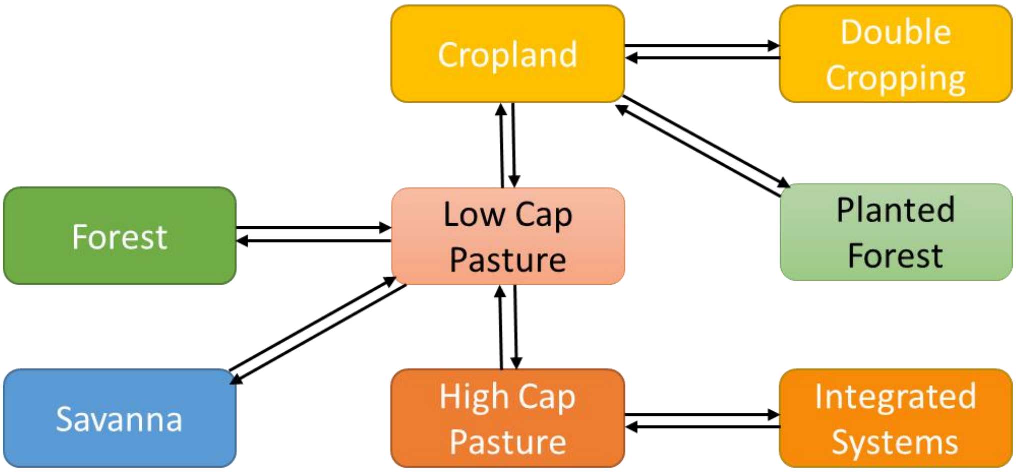

Figure 3-7 – Allowed land use transitions in COPPE-MSB

Each of these transitions have a set of parameters associated with the transition process, namely a cost, a CO_2 emission factor, and diesel use as the energy input. In addition, the human-made land cover classes (agriculture and livestock), may have other types of inputs such as fertilizers or lime for acidity correction. At this point, pesticides and herbicides are not modelled in BLUES.

As can be seen in Figure 3-7, there is a total of seven bi-directional land use transitions in BLUES. These transitions that reshape the current land use map in future timesteps are selected based on the transition costs. In emissions-constrained scenarios, the model also considers the net greenhouse gas emissions of a transition, measured as the difference in carbon stock before and after the transition. Figure 3-8 shows an example of a land use transition process called *Conv_F2U*, which represents conversion of forests to low-capacity pastures. As mentioned before, these are basically unmanaged, extensive rangelands used for grazing, typically supporting less than 0.7 AU/ha (Section 3.3.2.3). The figure shows a process that takes one hectare of forest as input, and outputs one hectare of low-capacity pasture, at a certain operational cost. The process also takes diesel as an additional (secondary) input, which represents the fuel used to power the transition via machines operating at an efficiency η. The process also adjusts constraints keeping track of each land cover type area by subtracting 1 ha from forest land an adding 1 ha to low-capacity pastures. These individual land cover type constraints must then always add up to the total land in the given region.

Finally, the process emits an amount of CO_2 equivalent to the difference in carbon stock between the input and output land use classes. Deforestation creates a positive net flow of CO_2 since the carbon stock in forests is generally larger than that in low-capacity pastures in Brazil, indicating the process to be a net source of CO_2. Negative CO_2 flows indicate sequestration by a process that is a net sink, such as afforestation or conversion of low- to high-capacity pastures. CO_2 emissions and sequestration are modelled as instant spikes that occur at the time of the transition. Although this is not an accurate representation, it is a shortcoming dictated by the architecture of the MESSAGE framework, which does not easily lend itself to carrying over stocks between timesteps. However, on a long-term basis, the flows do converge, which limits the distortions of this feature. Nonetheless, it is important to keep it mind that this makes the model overoptimistic on the potential for CO_2 sequestration through afforestation, especially in the near-term.

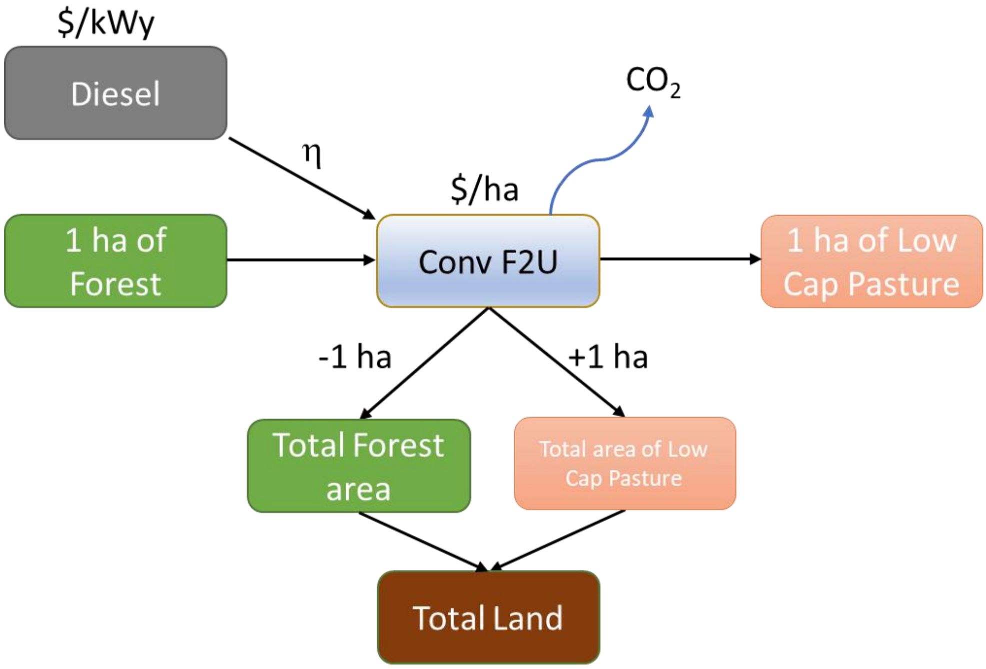

Figure 3-8 – Example of a land use conversion process in BLUES, showing deforestation to create low-capacity pastures.

In the real world there are limits to the extent to which transitions occur. It is unrealistic to think that in a single five-year time step all forest or savanna could be converted to low-capacity pastures by deforestation, or that all single-cropped areas could suddenly become double-cropped areas. Therefore, constraints are introduced to limit the area allowed to transition between different land cover types in a given time step. The upper bound on each transition is set as a proportion of the 2010 area of a given land cover type, as shown in Table 3-4. The values were taken from the listed references from current trends. Where a credible reference for current trend was unavailable, a value was chosen based on an ad hoc decision as indicated. As more data becomes available, theses constraints can be refined.

Table 3-4 – Constraints imposed as upper bounds on land cover transitions in BLUES

From	To	Amount per year (%) *	Reference
Forest	Low Cap Pasture	0.3	- 1.5x current rate North, Northeast and Mid-West regions - PRODES used as proxy for North, Northeast and Mid-West regions (INPE, 2017) - Based on recent values from SOS Mata Atlantica[a] for

			Southeast and South
Low Cap Pasture	High Cap Pasture	3	
High Cap Pasture	Integrated Systems	3	Based on current rates (ad hoc)
Low Cap Pasture	Cropland	1	Based on current rates (ad hoc)
Cropland	Dbl Crop	0.5	Based on current rates as estimated from IBGE (2018)
Cropland	Planted Forest	0.5	Based on current rates as estimated from IBGE (2018)
Savanna	Low Cap Pasture	0.6	(MMA, 2018)
Low Cap Pasture	Forest	0.3	Same as deforestation
Low Cap Pasture	Savanna	0.6	Same as deforestation

*** Values shown are national averages of regional values of starting land use class**
Notes: [a] https://www.sosma.org.br/projeto/atlas-da-mata-atlantica/dados-mais-recentes/

3.3.2.6. GHG emissions from land use transitions

The conversion of natural lands to anthropogenic use may cause CO_2 emissions. This happens when the natural land class has a higher carbon stock than the land use class to which it is converted, and the carbon present in the original land use class is not sequestered in wood harvested for uses other than combustion. The resulting emissions are the difference in total carbon stock between the original land cover type and the new land cover type, minus the wood harvested. Therefore, it is necessary to calculate the total carbon stock in each land cover type modelled in BLUES, and also the harvestable wood present in the native biomes, in each region. There is significant uncertainty in these parameters, originating in i) the great regional and local variability in carbon stock, and ii) the inherent uncertainty of different methods used to calculate the stock (BATLLE-BAYER et al., 2010; BECKNELL et al., 2012).

The method to estimate regional average values for each transition modelled in BLUES was done following these steps:

1. Estimation of average above- and below-ground biomass carbon content for each land cover type in each region for each cost class,
2. Estimation of harvestable wood for each land cover type in each region for each cost class,
3. Estimation of average soil organic carbon (SOC) for each land cover type in each region for each cost class,

4. Aggregation of 1 and 2 into an average total carbon stock for each land cover type in each region for each cost class,
5. Calculation of the net emissions in each modelled land use transition as the difference between the above-found values for the original and new land cover types in the modelled transitions.

3.3.2.6.1 Step 1: Estimating above- and below-ground biomass carbon content

We start with an estimate of the native carbon stock of native land cover types, which is based on a map of potential above-ground biomass (AGB) and below-ground biomass (BGB) of native vegetation developed by CSR-UFMG (SOARES-FILHO et al., 2016), shown in Figure 3-9. It is important to note that this map is a reconstruction of native vegetation based on literature review, expert consultations and modelling results, and some of the areas have long been transformed to human use[21].

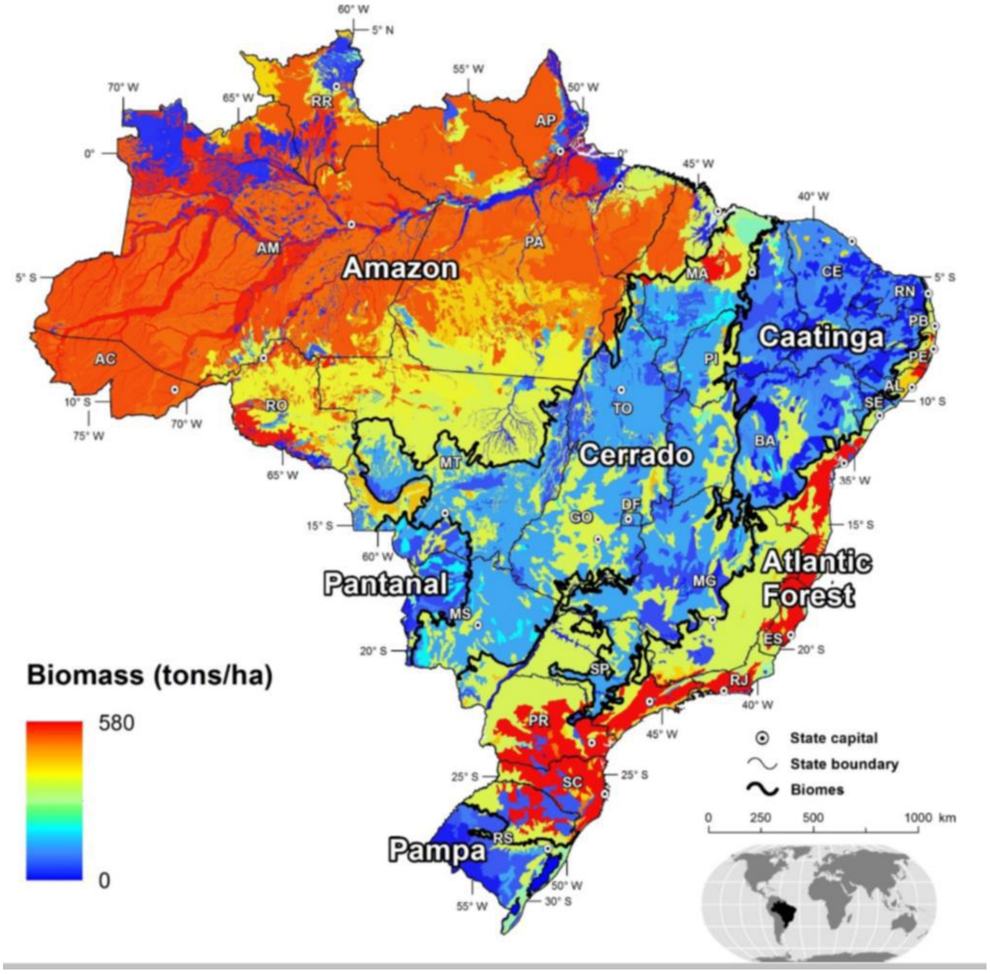

Figure 3-9 – The CSR-UFMG map reconstructing standing biomass of native vegetation in Brazil

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[21] The uncertainties in these quantities are therefore quite significant, and the results are used with caution, and will be subject of continuing research in the future, as well as sensitivity analyses. For more information see http://maps.csr.ufmg.br/

Built by the author based on SOARES-FILHO et al. (2016)

This biomass map was overlaid with a regional map of the BLUES sub-regions, the map of BLUES land use classes (Figure 3-6), and a map of the 6 cost classes (Section 3.3.6), so that a land-area weighted average of the biomass content in the AGB and BGB could be calculated for each native land cover type in each region for each cost class. From this, the carbon content of a land use class *lc* of cost class *cc* in region *r* is given by:

$$C\_stock_{r,lc,cc} = \frac{ABGB_{r,lc,cc} * LC\_Area_{r,lc,cc}}{\sum_{cc} LC\_Area_{r,lc,cc}} * BCC \qquad \text{Equation 2}$$

Where *ABGB* is the above- and below-ground biomass; *LC_Area* is the area of land class *lc* in region *r*; the denominator is the total area of a land class *lc* in region *r*. Finally, *BCC* is the biomass carbon content denoting the share of the above- and below-ground biomass that is carbon (the share of carbon atoms in the tissue). A generally accepted assumption that about 50% of biomass is comprised of carbon (SOARES-FILHO et al., 2016) was used so as to transform this map into a carbon stock map.

The resulting values for AGB and BGB carbon content of native land use classes in the five regions of BLUES is shown in Table 3-5.

Table 3-5 – Above- and below-ground biomass carbon content of native land use classes in the five regions of BLUES (in tC/ha)

Unit = tC/ha	Forest	Forest in PA	Savanna	Savanna in PA
NO	168.0	172.0	56.5	34.5
NE	89.5	123.0	32.5	29.5
SE	99.5	110.5	55.0	33.5
SU	110.5	124.5	17.5	18.5
CO	107.0	132.5	61.0	42.5

3.3.2.6.2 Step 2: Estimating share of harvestable wood

Because some of the wood is removed during the transition from the natural land cover to lo-cap pastures, the carbon content of this wood is not emitted, but remains in the harvested wood as timber, which is assumed to not be burned. Thus, it is necessary to estimate the shares of AGB versus BGB in each land cover type in each region, and then to estimate the share of AGB that is harvestable timber. Most of the studies in the literature review of the previous section reported both AGB and BGB rather than an aggregated total biomass content. The average shares for each was then used to split the values in the map in Figure

3-9 into above- and below-ground biomass. Table 3-6 shows the share of total biomass that is above ground for the native biomes in BLUES and for the biome clusters assigned to each region.

Table 3-6 – Share of biomass that is above ground in native land use classes and in select regions of BLUES

Forest NO	Forest CW-NE	Forest SO-SE	Savanna SO	Savanna NE	Savanna others
73%	84%	31%	60%	24%	34%

Now, if we know the share of above-ground biomass that is harvestable timber, we can deduct this value from the carbon emitted during the native vegetation clearing. CUMMINGS et al. (2002) report that about 82% of total above-ground biomass (TAGB) in Amazonian rain forests is 82%. However, for trees with diameter at breast height (dbh) greater than 50 cm, this number drops to between 30 and 38% depending on the type of forest. Likewise, Nascimento and Laurance (2002) found that the share of large trees (>10 cm dbh) comprised 81.9% of TAGB in 20 plots surveyed in Amazonia. However, for trees with >50 cm dbh, the share dropped to about 33%.

However, defining what is "harvestable" is not straight forward. It depends on local conditions such as forest composition and distance to roads. Defining an average value for large regions like the regions in BLUES is fraught with uncertainty. Hence, an ad hoc decision was made to make this value be 5% of above ground biomass. Although this only a portion of the actual timber content of Brazilian forests, a more accurate definition of this number is left for future research.

3.3.2.6.3 Step 3: Estimating soil organic carbon (SOC) content

In addition to biomass carbon, soil organic carbon (SOC) must also be included to provide an accurate value of carbon stock for each land cover type. The SOC in both native and anthropogenic land cover types was drawn from literature and clustered according to the biomes assessed. Table 3-7 shows the results of the literature review and the headings of the columns indicate the biome in which the referenced study was conducted, to which the clusters relate. The values for each cluster were then averaged and assigned to the five regions in BLUES according to the dominant vegetation for each land use class in a given region. Thus, the forests in the North region were assumed to be Amazon tropical rain forests, while those in the Center-West region were assumed to be dominated by what is known as the *Cerradão,* a sub-tropical forest not as wet as the Amazon. Likewise, savannas were assumed to be Pampas in the South region, *Caatinga* in the Northeast, and *Cerrado* savanna in the Center-West. The values for each column were averaged and these were the values for SOC assigned to the respective land use classes.

Table 3-7 – Results of literature review to estimate soil organic carbon (SOC) for native land cover types (in tC/ha)

SOC	Amazonia	Cerrado Savanna	Cerrado Forest	Atlantic Forest	Pampa	Caatinga	Source
	56.3						CARVALHO et al 2010
	74.1						CARVALHO et al 2011
				42.5			LEITE et al 2013
		52.9					MAIA et al 2010
						15.0	SAGRILO et al 2015
					25.6		SA et al 2010
		46.0	53.0				DE MIRANDA et al 2014
Mean	**65.2**	**49.4**	**53.0**	**42.5**	**25.6**	**15.0**	

A similar process was repeated for anthropogenic land cover types. Table 3-8 shows the results of the literature review conducted for that purpose. The mean of the values found for each land cover types was assigned as the value for SOC of the respective land use class in BLUES.

Table 3-8 – Results of literature review to estimate soil organic carbon (SOC) of anthropogenic land cover types (in tC/ha)

SOC	Cropland	Lo Cap Past	Double Crop	Hi Cap Past	Int Syst	Planted Forest	Source
	55.6						MAIA et al 2010
		59.4		68.3			ROSA et al 2014
		45.0		59.2			Costa et al 2009
		56.5		62.6			ASSAD MARTINS 2015
	51.5						CARVALHO et al 2009
			66.4	68.0	72.4		CARVALHO et al 2014
						65.7	FIALHO et al 2014
		55.7		66.4			
					61.4		CARVALHO et al 2010
					62.8		
					73.0		

Mean	**53.5**	**54.1**	**66.4**	**64.9**	**67.4**	**65.7**

3.3.2.6.4 Step 4: Aggregating to average regional carbon stock estimates

To estimate the carbon stock of the land use classes in BLUES, the AGB, BGB, and SOC were added together, and the harvestable timber portion was subtracted from that total. Hence, the carbon stock of land use class *lc* of cost class *cc* in region *r* is given by the equation 3 where $HT_{lc,cc,r}$ is the harvestable timber content of land use class *lc* of cost class *cc* in region *r* as defined above.

$$C\_stock_{lc,cc,r} = AGB_{lc,cc,r} + BGB_{lc,ccr} + SOC_{lc,cc,r} - HT_{lc,cc,r} \qquad \text{Equation 3}$$

3.3.2.6.5 Step 5: Calculating net emissions in the land use transitions in BLUES

Since the ultimate goal of this carbon stock analysis is to estimate the emissions associated with land use transitions, these values were used to calculate the net emissions in each modelled transition in BLUES. This is calculated as the difference in the carbon stock between the original and the new land use type times a calibration factor *cf* used to adjust the average values in the calibration phase of the model to reported emissions from LUC in Brazil.

$$Net\_emiss_{lt,cc,r} = (C\_stock_t - C\_stock_{t-1}) * cf \qquad \text{Equation 4}$$

The calibration factor *cf* is set to 0.50 in the current implementation. The value was originally set to 1.0, but this resulted in AFOLU emissions that were almost twice those reported for the base year 2010 by the *3rd National Communication* (GofB, 2015a). Changing the calibration coefficient to 0.5 results in AFOLU emissions equivalent to 65% of those reported for the base year 2010. Because carbon stock is subject to high uncertainties (see Section 0), this is one aspect that deserves a lot more research and careful assessment in order to determine the optimal value in order to more accurately reproduce historical values. In fact, *cf* should vary for each region in BLUES. However, this is beyond the scope of this thesis and is left for future research. The resulting values of the current implementation for the CO_2 emissions of each transition in each region are shown in Table 3-9.

Table 3-9 – CO_2 emissions (sequestration) in land use transitions in BLUES.

tCO2/ha	NO	NE	SE	SU	MW
F2U	471	123	161	201	185
U2H	-43.1	-43.1	-43.1	-43.1	-43.1
H2I	-16.5	-16.5	-16.5	-16.5	-16.5
U2C	2.30	2.30	2.30	2.30	2.30
C2D	47.3	47.3	47.3	47.3	47.3
C2P	-45	-45	-45	-45	-45
S2U	9	-79	3	-134	25

Created by the author. Positive values = emissions

3.3.2.6.6 Uncertainties in estimation of carbon stocks

Estimating carbon stock of land cover types for large regions involves averaging highly variable local values that also carry methodological uncertainties embedded in the measurements of single parameters in highly complex systems that defy classification into a single uniform category such as “forest” or “savanna”, resulting in wide ranges of values reported in the literature. For example, BECKNELL et al. (2012) report global estimates of aboveground biomass for seasonally dry tropical forests spanning an order of magnitude between 28 to 390 Mg/ha. For Brazil, estimates for total aboveground biomass in the Amazon have been reported between 155 and 555 Mg/ha (CUMMINGS et al., 2002), while Nascimento and Laurance (2002) cite a previous study by HOUGHTON et al (2000) that estimated total standing biomass in Brazilian Amazonia to be in the range of 39 to 93 Pg of C, a factor of 2 variation.

Nonetheless, the parameters that determine total biomass in a given biome are relatively well known, so it is possible to make somewhat accurate estimates of specific spots or sites. Based on literature with field, soil and meteorological data, SOARES-FILHO et al. (2016) generated the map shown in Figure 3-9. Aggregating the highly spatial data depicted in the map to the 5 macro-regions in BLUES means making compromises on accuracy of the carbon stock value implemented in the model[22]. Therefore, this value must be calibrated against observed values for the dependent variable that is being examined, in this case the final CO_2 emissions associated with land use change. The land use emissions reported by Brazil to the UNFCCC in its *3rd Communication* (GofB, 2015a) result from detailed spatially explicit information that is referred to in IPCC parlance as a Tier 3 type of assessment, based on remote sensing and other techniques as explained in the document appendix. Thus, the sum total of the emissions for Brazil as a whole, which is what is reported in the *3rd*

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[22] This is a compromise exacted by the hard-linking of the land use system to the rest of the modelling framework.

Communication, can be used to calibrate a factor to adjust the national total land use CO_2 emissions from BLUES to the reported values for CO_2 emissions.

This multiplier, or coefficient, was implemented in the exogenous estimates of carbon stock, and originally set to 1, which yielded base year 2010 AFOLU emissions much higher than those reported in the *3rd Communication*, higher by a factor of 2. Therefore, the value was next set to 0.50, which caused AFOLU emissions from BLUES for the base year 2010 to drop to 65% of those reported in the *Communication*, suggesting there are 2nd order effects in the choice of this value. That is, the choice of this value affects other sectors, which in turn affect AFOLU emissions, in such a way that it is hard to gauge what exactly the value of the factor should be. Probably, a few rounds of judicious trial-and-error would be enough to calibrate the model appropriately to reproduce 2010 AFOLU emissions, and eventually, the emissions from land use change exclusively. This, however, is left for future work since not only the base year emissions must be correct, but the 2nd order effects must be well understood to prevent unwanted changes to other sectors.

3.3.3. Modelling agricultural processes

We turn now to the second basic set of data involved in modelling land use, namely the conversion processes that use land as their main input and produce agricultural commodities as outputs. As mentioned before, these processes are governed by dynamics in the agricultural sector, the main driver behind land demand. Recapitulating, the agricultural sector in BLUES is represented by two basic types of such processes:

1. Processes that convert land in one state into another state, and
2. Processes that convert land into agricultural products.

The processes in item 1 have been explained above (Section 3.3.2.5). The processes in item 2 latter are those that produce the products desired by society and operate with a given efficiency (the agricultural yields), and at a given production cost that is different for each region and product.

Two agricultural sub-sectors are modelled in BLUES: livestock production and crop production. These are modelled as a set of processes much like the land conversion process shown earlier. We look at livestock first, and then at crop production. The next section looks at the livestock production processes, describing its yield and cost parameters. The following section looks at agricultural processes of crop and livestock production. Next, regional cost variations are explained in Section 3.3.6. Then, the integrated systems are explained. Finally, the GHG emission factors are explained in the final section of this chapter.

Table 3-10 shows the list of agricultural processes in BLUES, along with their input and output commodities. Each process also outputs CO_2, CH_4 and N_2O, according to emission factors drawn from literature when available, or as default values when not. The emission factors for GHGs are described in the Section 3.3.8 As can be seen, first there are the crop production processes that output food, fiber and energy crops from both single- and double-cropped land. There is also a residue-burning process which burns any unutilized agricultural residue to transform it to CO_2. Then there are livestock processes, which include the low- and high-capacity pastures as well as the integrated systems of livestock-crop-forestry production.

Table 3-10 – Agricultural processes modelled in BLUES

Process name	Input	Output
Crop_[food and fiber class]	Land (kha), diesel (MWy), urea (kt)	Total production in kt of crop classes, where the food and fiber crop classes are: Wheat, Fruits, Soybeans, Maize, Cereal, Vegetables, Roots, Pulses, Oilseed, Nuts, Sugarcane, Coffee, Fiber and Rice
Crop_[energy crop class]		Total production in Mwy of Woody (Eucalytptus) and Grassy (elephant grass) bioenergy feedstocks
dblCrop_Soybeans_Maize		Soybeans, Maize
dblCrop_Soybeans_Wheat		Soybeans, Wheat
Residue_burned		residue burning
Crop_Wheat_HY1		Higher Yield Wheat
Crop_Wheat_HY2		Highest Yield Wheat
Crop_Soybeans_HY1		Higher Yield Soybeans
Crop_Soybeans_HY2		Highest Yield Soybeans
Crop_Maize_HY1		Higher Yield Maize
Crop_Maize_HY2		Highest Yield Maize
Crop_Cereal_HY1		Higher Yield Cereal
Crop_Cereal_HY2		Highest Yield Cereal
Crop_Oilseed_HY1		Higher Yield Oilseed
Crop_Oilseed_HY2		Highest Yield Oilseed
Crop_Sugarcane_HY1		Higher Yield Sugarcane
Crop_Sugarcane_HY2		Highest Yield Sugarcane
Livestock_Cattle_Meat_LoCap		Beef cattle
Livestock_Cattle_Meat_HiCap		Beef cattle
Livestock_Cattle_Meat_intSys_CL1		Beef cattle, maize
Livestock_Cattle_Meat_intSys_CL2		Beef cattle maize, soybeans
Livestock_Cattle_Meat_intSys_CLF		Beef cattle, maize, soybeans, wood
Livestock_Cattle_Milk_LoCap		Milk
Livestock_Cattle_Milk_HiCap		Milk
Livestock_Cattle_Milk_CL2		Milk, maize, soybeans
Livestock_Others		Other livestock (pigs, chicken, goats, sheep)

A note on the regional cost variations explained in Section 3.3.6 is needed here, that the variations are applied on a benchmark cost that is representative of the process on a national basis. In other words, regional cost variations are applied on a national benchmark for each process for which data is available. It is important to note that the cost parameters for agricultural products in BLUES do not affect demand for the products, since demand is exogenously set. Except for bioenergy feedstocks, whose demand is driven by cost-based competition between technologies that meet energy service demand, some of which use bioenergy feedstocks. Thus, the cost of bioenergy crops does play a part in determining relative costs vis-à-vis other energy commodities.

3.3.4. Livestock production systems

Livestock production takes one hectare of land and outputs the number of animal units consistent with the type of pasture the process is representing. Figure 3-10 shows a schematic of the beef cattle production chain, from pasture to final product. It takes as input 1 ha of pasture and outputs a number of animal units depending on the carrying capacity of the pasture it takes as input. This animal unit then goes to slaughter at a rate (% of herd) also consistent with the carrying capacity of the initial pasture, since animals raised on well-maintained pastures have a shorter time to slaughter and a higher carcass weight than those raised on low-capacity pastures (CARDOSO et al., 2016). Thus, the final yield (in kg of meat per hectare) will vary according to the type of livestock production system.

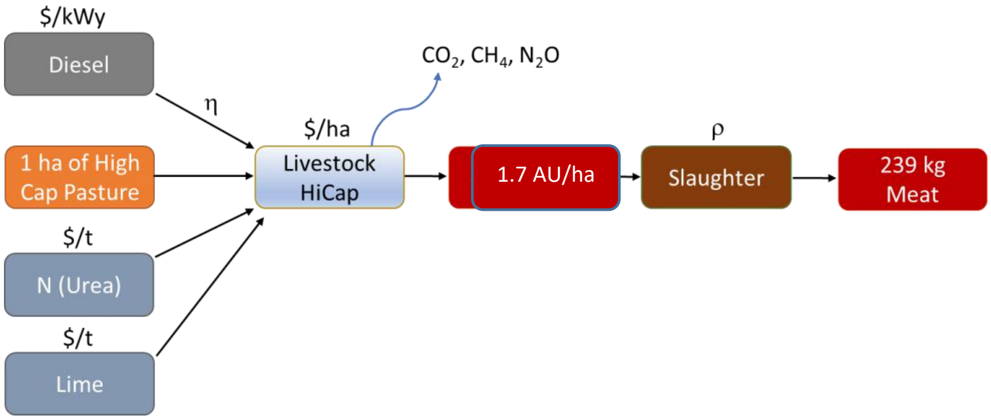

Figure 3-10 – Representation of the beef cattle production chain

Three types of livestock production systems are modelled in BLUES: low-capacity pastures, high-capacity pastures and integrated systems. Low-capacity pastures are unmanaged, often degraded, pasture areas in which animals are set free to fend for themselves, typical of low-density extensive livestock production systems in Brazil (CARDOSO et al., 2016). In contrast, high-capacity pastures are managed pastures in higher-input production systems that typically reform the pasture once every five to ten years, demand diesel, fertilizer and lime, and use exotic foraging crops such as Guinea grass, and better bovine crosses such as Nellore. The parameters of these two production systems for diesel, fertilizer and lime inputs, productivity and emissions were taken from Scenarios 1 and 4 respectively in CARDOSO et al. (2016). These parameters are shown in Table 3-11.

Table 3-11 – Input parameters of low- and high-capacity pasture systems modelled in BLUES

Livestock production system	Stocking rate (LU/ha)	Carcass weight (index)	kg carcass per ha	Area per kg carcass (m2)	Diesel Use (L/ha)
Low Cap Pasture	0.5	1	31.2	320.1	0
High Cap Pasture	1.7	1.3	201.7	49.59	6.46

Source: adapted from CARDOSO et al. (2016)

As can be seen, the transition from low- to high-capacity pasture systems requires higher management and inputs. Not only is the stocking rate higher in high-capacity pastures, but the carcass yield is also higher, meaning the high-capacity system delivers a lot more product per hectare than the low-capacity system. Milk production systems are analogous, with the difference that the output of the pastures does not go through the animal unit or slaughter rate steps, but directly to milk, so that the input of milk production is 1 ha of pasture and the output is tons of milk consistent with the type of pasture the cows are grazing on.

The stocking rates of the two pasture types was calculated based on the stocking rates of Brazilian pastures as given by the CSR pastures map (BARBOSA ALVIM et al., 2015) (Section 3.3.2.3). The average stocking rate for the base year was calculated as a weighted average of the stocking rate over the area of each of the categories of livestock density given in the original land use map.

The average (across cost classes) region-specific base-year stocking rates of the three systems modelled in BLUES are shown in Table 3-12. The areas for each pasture type were shown in Table 3-2 in Section 3.3.2.3.

Table 3-12 –Stocking rates of the different types of livestock production systems in each region in BLUES Average across cost classes shown.

AU/ha*	NO	NE	SE	SO	CW
Low-Capacity Pastures	0.88	0.79	0.86	0.88	0.88
High-Capacity Pastures	1.40	1.34	1.45	1.68	1.31
Integrated Systems	2.50	2.50	2.50	2.50	2.50

***AU = animal unit = 450 kg of live weight**

Source: original results

3.3.5. Crop production systems

Much like livestock production, crop production takes one hectare of land and outputs a certain mass of crop product at a certain cost consistent with the yield potential in each cost class at the given region. Crop yields were calculated from data from IBGE's *Produção Agrícola Municipal* (PAM) (IBGE, 2017a) series for planed area and production per crop and per region. Except for the six explicitly-modelled crops in BLUES, crops depicted in the CSR map used as the basis of the initial land use map we aggregated according to the definition and classification of agricultural commodities used by the UN Food and Agriculture Organization (FAO) (FAO, 2017a).

Table 3-13 shows the resulting crops and crop categories included in the BLUES model.

Table 3-13 – Crops and aggregated crop categories included in the BLUES model

Crop category	Description
Soybeans	*Glycine max*
Sugarcane	*Saccharum spp*
Maize	*Zea mays* and other variants cultivated in Brazil
Rice	*Oryza spp*
Wheat	*Triticum spp*
Coffee	Both arabica and robusta
Cereal	Barley, popcorn, rye, oats, millets, sorghum, triticale
Fiber	Cotton, jute, flax, rami
Fruits	Edible perennial and seasonal fruits; dominated by oranges and bananas
Nuts	Mainly cashew nuts, but also Brazil nuts, and others
Oilseed	Cottonseed, castor bean, canola, palm
Pulses	Beans, chickpeas and lentils
Roots	Cassava, potatoes, sweet potatoes
Vegetables	Tomatoes, leaf vegetables, *Brassica spp*
Grassy biomass	Modelled as *Miscanthus* or elephant-grass (*Pennisetum spp*); several others exist in Brazil
Woody biomass	Eucalyptus or Pinus; modelled as Eucalyptus

Table 3-14 shows the benchmark yields for the crops modelled in BLUES in each sub-region of the model. As mentioned before, the benchmark cost is the one assigned to Cost Class C, with the others varying according to a multiplier index (Section 3.3.6). Thus, crop yield also varies with the cost class it is located in, given that agricultural productivity is one of the components of the cost parameter.

Table 3-14 – Benchmark yields of agricultural crops in each region in BLUES (Unit = t/ha)

	North	Northeast	Southeast	South	Center-West	Crops aggregated
Soybeans	2.89	2.86	2.85	2.90	3.02	-
Sugarcane	64.13	55.76	83.88	74.91	81.77	-
Maize[a]	2.57	1.70	5.17	5.73	4.47	-
Wheat[b]	-	-	2.68	2.83	2.84	-
Rice	2.68	1.34	2.79	6.43	2.99	-
Coffee	0.92	0.97	1.41	1.68	1.37	-
Cereal	2.54	2.54	2.54	2.54	2.54	Oats, Rye, Barley, Sorghum, Triticale
Fruits	10.66	16.19	20.12	14.20	15.21	Pineapple, bananas, Cocoa, Coconuts, Figs, Guava, Oranges, Lemons, Apples, Papaya, Mango, Passion fruit, Quince, Pears, Peaches, Tangerines, Grapes
Vegetables	8.94	17.36	21.61	18.07	28.79	Avocado, hearts-of-palm, garlic, peanuts, onion, watermelon, melon, tomato
Pulses	0.58	0.30	2.50	1.79	2.35	Beans, peas, broad beans
Roots	17.01	18.67	20.62	18.12	24.61	Sweet potato, potato, cassava
Nuts	0.76	0.13	1.61	2.29	0.38	Walnuts, cashew nuts, coconuts
Oilseed	5.86	2.42	6.54	3.87	4.98	Coconut, peanut, sunflower, flax
Fiber	1.99	1.65	3.10	2.15	3.55	Cotton, jute, agave, rami, malva

a) Maize data for first annual harvest shown. b) The North and Northeastern regions are outside the wheat agroecological zone.

Source: prepared by the author based on data from (IBGE, 2017a)

3.3.6. Cost assessment

The initial land use maps provide information about *where* agricultural and forestry products can be produced in the base year. Since BLUES is a cost-optimization model, an estimate of production costs must be provided to the model for each commodity. Agricultural costs are a product of many variables, some of them difficult to quantify on a macro-region scale given their local characteristics. Moreover, there are many parameters that influence cost formation of agricultural products, many of which are very local in nature, while others are nationally and even globally determined. In many cases, data is unavailable or highly uncertain. Thus, to reduce complexity and increase transparency, a simplified approach was chosen.

In the absence of direct cost data, ROCHEDO (2016) developed a methodology for a proxy based on distance to main cities and edaphoclimatic productivity. The same general methodology is followed here, using the same map of travel distance (UNEP, 2017b), but a different edaphoclimatic productivity map, namely the *Crop suitability index (class) for high input level rain-fed cereals*[23] baseline map (FAO, 2017b). These global maps were cropped and reprojected in QGIS to the same dimensions as the CSR-UFMG maps, and then converted to a PCRaster (.map) format using GDAL[24] Translate function so they could be used in PCRaster.

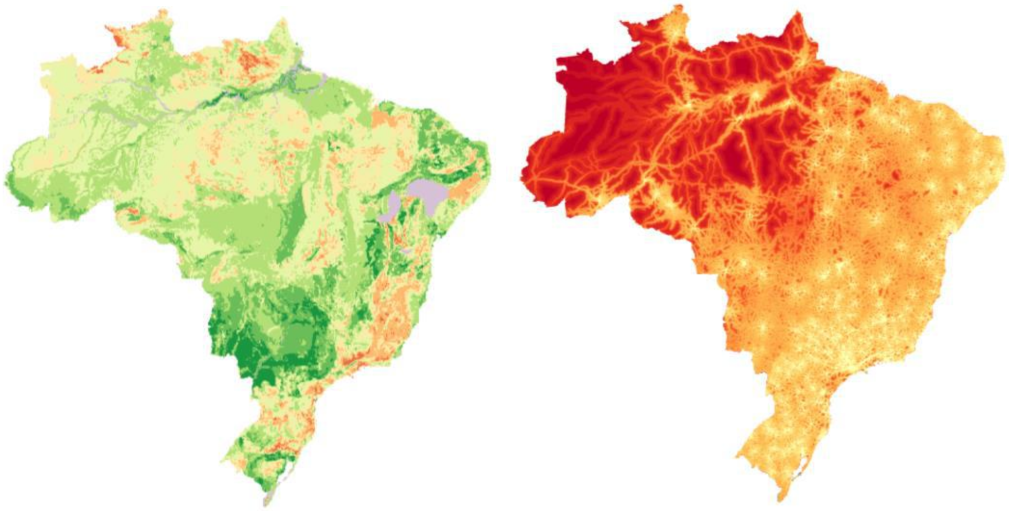

Figure 3-11 –Productivity (left) and travel time (right) maps used for agricultural production cost assessment in BLUES.

Sources: GAEZ-IIASA (2017) and UNEP (2017b)

In PCRaster, the values of the cells in the scalar maps were aggregated into intervals representing classes in nominal maps. The index levels of the FAO map were divided into seven classes of relative suitability, and the UNEP map into seven classes of relative travel time according to Table 3-15. The last class (Class 8) of the suitability maps have two large areas where no data is provided, in the region dominated by the semi-arid conditions of the Brazilian *caatinga* biome, as this map is for rainfed agriculture only. In spite of the adverse edaphoclimatic conditions there, irrigated agriculture of high-value added crops (mainly

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[23] For now, this map for medium-input rainfed cereal productivity is used as a proxy for productivity for all crops. Implementation of separate suitability maps for each crop and management level is left for future research.

[24] The Geospatial Data Abstraction Library (http://www.gdal.org/).

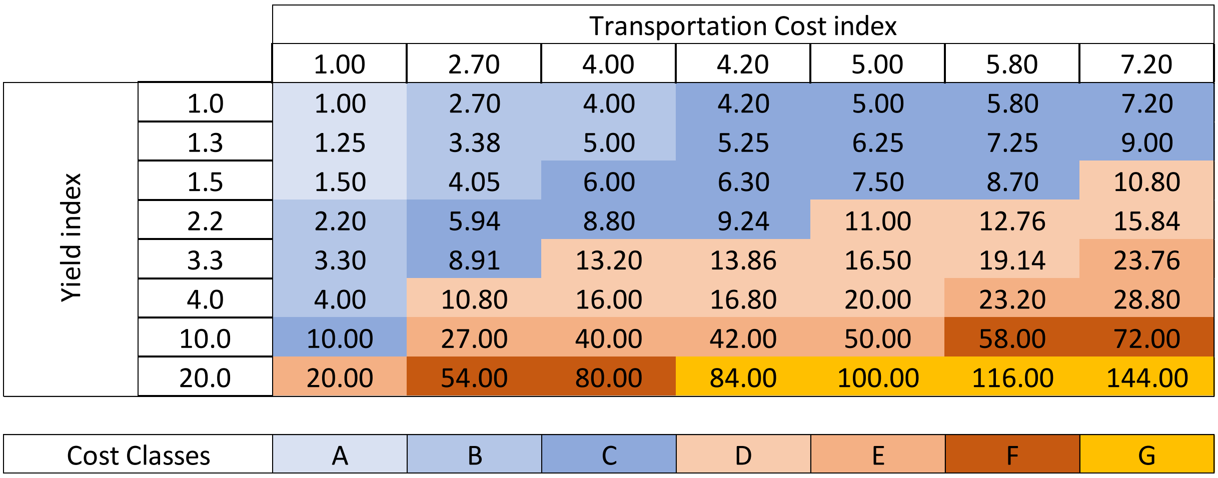
fruits) do take place. In order to capture this high cost production, we assigned a very high relative cost for production there. This high value cost is somewhat attenuated by the fact that large cities exist inside or on the edge of these areas, and this is reflected in the composite production cost map. Urban areas and water bodies were also removed from the map via a mask produced from the respective CSR-UFMG map classes.

Table 3-15 – Aggregation from original data of edaphoclimatic suitability and travel time

Category	Soil suitability		Travel Time		
	Original classes	Relative value	Original classes	Aggregation (hours)	Relative value
1	1	1.00	1 – 4	< 2	1.0
2	2	1.25	5 – 6	2 – 6	2.7
3	3	1.50	7 – 8	6 – 12	4.0
4	4	2.20	9	12 – 25	4.2
5	5	3.30	10	25 – 32	5.0
6	6	4.00	11 – 12	32 – 60	5.8
7	7	10.0	13 – 14	60 – 180	7.2
8	8	20.0	-	-	-

By multiplying the relative values of each map for each grid cell, we end up with 56 classes of relative production costs, which are then aggregated into seven cost classes (A-G), by identifying cutoff values, as shown in Table 3-16. Class G encompasses a very small extent and is restricted to either very unsuitable or very remote locations.

Table 3-16 – Aggregation of relative agricultural production costs into six classes



		Transportation Cost index						
		1.00	2.70	4.00	4.20	5.00	5.80	7.20
Yield index	1.0	1.00	2.70	4.00	4.20	5.00	5.80	7.20
	1.3	1.25	3.38	5.00	5.25	6.25	7.25	9.00
	1.5	1.50	4.05	6.00	6.30	7.50	8.70	10.80
	2.2	2.20	5.94	8.80	9.24	11.00	12.76	15.84
	3.3	3.30	8.91	13.20	13.86	16.50	19.14	23.76
	4.0	4.00	10.80	16.00	16.80	20.00	23.20	28.80
	10.0	10.00	27.00	40.00	42.00	50.00	58.00	72.00
	20.0	20.00	54.00	80.00	84.00	100.00	116.00	144.00

Cost Classes	A	B	C	D	E	F	G

Each cost class *c* is assigned a cost multiplier δ that adjusts the cost of a benchmark regional average cost for each of the processes in BLUES, according to Equation 5.

$$vom_{i,r,c} = \delta_{r,c} * \overline{c_{\iota,r}} \qquad \text{Equation 5}$$

Where $vom_{i,r,c}$ is the variable operational cost of process I in region r in cost class c; $\delta_{r,c}$ is the cost multiplier in region r of cost class c; and $\overline{c_{\iota,r}}$ is the benchmark cost of process I in region r. The values assigned to the multiplier $\delta_{r,c}$ are shown in Table 3-17. As can be seen, the regional average benchmark cost of process I is assigned to cost class C, while cost classes A and B have lower costs and classes D, E, and F have higher costs.

Table 3-17 – Values of cost multiplier $\delta_{r,c}$ used to adjust costs of processes in the different cost classes in BLUES

Cost Class	$\delta_{r,c}$
A	0.8
B	0.9
C	1
D	1.2
E	1.7
F	2.5
G	3.5

It should be noted that, although the parameter r is shown in the equation, it is not activated, meaning there is no regional variability of the cost multiplier parameter in this version of BLUES. GARAFFA et al. (2017) showed there is significant variability across regions on the investment and operation costs of large infrastructure projects in Brazil; reported estimates for the regional multiplier values to adjust total project costs against international parity benchmark. Although an analogous methodology could be developed for the agricultural sector, this has not been done to date, and is left for future research. Thus, for the time being there is no regional variation in the cost multiplier. However, as will be explained in Section 3.3.6, the benchmark costs are defined for each sub-region in BLUES, so that the final cost implemented is indeed regionalized.

The geographical area of each cost class is implemented as an upper bound of the extent to which a process can be deployed at the cost level defined by each cost class. The resulting map of the distribution of the grid cells making up each of the production cost classes is shown in Figure 3-12. As expected, the vast majority of the low production cost areas are in the Center-South region, home to the most fertile soils, flat plains, and large cities in the country. The areas close to the coast also benefit due to proximity to the large coastal urban centers and infrastructure. This in spite of the low productivity prevalent in the Northeastern region.

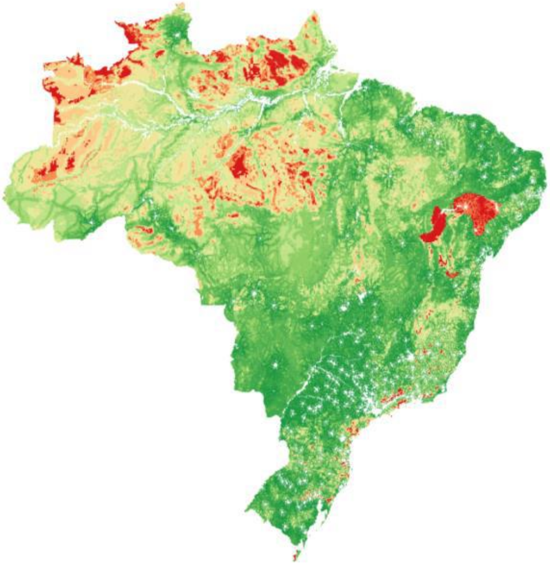


Figure 3-12 – Relative production costs map resulting from the combination of transportation costs and potential yield

Source: Prepared by the author (see text)

The area of each cost class for each land use class is shown in Table 3-18. What is immediately apparent is that Brazil still has a little less than half of its 852-Mha territory covered with natural forest remnants (around 400), and around 14% with natural savanna remnants (122 Mha). On the other hand, cropland and pastures cover around a third of the territory (263 Mha), implying that small yield increases in agriculture and livestock sectors can lead to large areas of spared land.

Table 3-18 – Area of each land use class in Brazil for the base year of BLUES (2010) (Unit = Mha)

	Cropland	Double Cropping	Low Cap Pasture	High Cap Pasture	Forest	Forest in PA	Savanna	Savanna in PA	Planted Forest
A	12.99	3.04	29.43	9.42	7.14	0.46	13.50	0.40	1.60
B	17.84	3.72	73.52	21.16	35.45	4.39	39.37	2.20	2.91
C	9.12	1.79	41.36	18.36	96.79	64.85	43.43	7.10	1.17
D	1.54	0.09	10.92	4.78	66.54	102.13	8.46	2.06	0.46
E	0.12	0.00	2.24	0.26	4.41	15.17	1.65	0.22	0.07
F	0.06	0.00	1.92	0.00	0.52	2.54	3.65	0.08	0.01
Total	41.67	8.64	159.39	53.98	210.84	189.54	110.05	12.06	6.22

Source: own modelling, original results

3.3.6.1 Estimating cost of livestock production

Livestock production costs data points were taken from ANUALPEC (2013), which provides cost data on livestock production for extensive systems on 500 ha and 5000 ha, and semi-intensive systems on 5000 ha, in municipalities with high livestock activity. These were grouped by region into low-capacity pastures with less than 0.9 AU/ha, and high-capacity pastures with more than 0.9 AU/ha, and then averaged to give the regional average cost of livestock production. This cost was implemented into BLUES as a variable cost parameter (*vom*). Animals were added as calves to maintain or grow the herd in addition to replacement in line with the slaughter rate. The cost of calves was set at US$416, based on data from SENAR (2013).

As mentioned before, the benchmark cost is the one assigned to Cost Class C, with the others classes varying according to a multiplier index. Thus, livestock yield also varies with the cost class it is located in, given that productivity is one of the components of the cost parameter. The resulting livestock production variable costs for each system are shown in Table 3-19 for both meat and milk production. In addition, they were adjusted for each cost class (A-F) as explained in Section 3.3.6.

Table 3-19 – Regional distribution variable cost of different livestock production systems in BLUES

Unit	Product	Production Process	NO	NE	SO	SE	CW
US$/head	Bovine Meat	Low-cap pasture	572	536	574	636	577
		High-cap pasture	787	765	821	967	758
		Integrated System	894	870	916	1010	859
US$/t milk	Bovine Milk	Low-cap pasture	877	789	523	364	638
		High-cap pasture	741	667	442	308	539
		Integrated System	842	759	493	322	611

3.3.6.2 Estimating cost of crop production

This agricultural production happens at a cost, which is implemented as variable costs in BLUES. The data used to estimate costs of crop production in the base year 2010 came from a combination of AGRIANUAL (2013) and IBGE (2017a) data, following these steps:

1. First, IBGE data for production and planted area for each crop from the *Produção Agrícola Municipal* (PAM) series (IBGE, 2017a) was grouped by region and the yield was calculated by dividing production by area, taking care to account for double cropping (see below).
2. Then, the AGRIANUAL data for yield and associated cost was grouped by region and averaged to give mean yield per region.
3. Finally, the average costs per region calculated in step 2 from AGRIANUAL data were adjusted by cross-multiplication to the yields from IBGE calculated in step 1.

Step 3 step was necessary for two reasons. First, AGRIANUAL cost data is gathered for specific locations for specific yield levels. Hence, they do not necessarily reflect average conditions for Brazil, and the adjustment sometimes raised and other times reduced the production cost of crops. Second, not all crops reported by IBGE are included in AGRIANUAL, so the missing crops were mapped via this calculation done in Step 3.

Table 3-20 shows the resulting benchmark costs which are then multiplied by the multiplier index value as described in Section 3.3.6. These costs are not calibrated to real world prices and, in some cases, may be above market prices. This is a result of the AGRIANUAL data set used, which assesses costs for specific regions delivering specific yields, which may not represent average conditions in Brazil. Calibrating these costs is left for future research as it is not a straight-forward exercise for a model that deals with averages across whole regions bigger than many countries.

Table 3-20 – Benchmark variable costs of agricultural crop production in each region in BLUES

Costs (US$/t)	NO	NE	SE	SU	CO
Wheat	--	--	334.1	208.3	213.1
Fruits	923.4	923.4	923.4	923.4	923.4
Soybeans	252.5	340.5	254.3	261.0	252.5
Maize	234.6	653.4	252.2	182.5	234.6
Cereal	223.5	622.6	240.3	173.9	223.5
Vegetables	560.1	560.1	560.1	560.1	560.1
Roots	1229	1229	1229	1229	1229
Rice	334.8	334.8	297.3	259.8	334.8
Pulses	618.2	618.2	618.2	618.2	618.2
Oilseed	55.2	74.4	55.5	57.0	55.2
Nuts	1637	1637	1637	1637	1637
Sugarcane	28.1	28.1	27.3	32.4	28.1
Coffee	1724.3	1724.3	1724.3	1724.3	1724.3
Fiber	3111.7	8668.2	3345.8	2420.9	3111.7
Woody	33.0	42.9	30.8	33.0	33.0

Source: prepared by the author based on data from AGRIANUAL (2013)

3.3.7. Integrated systems

Integrated Systems (IS) are the second largest contributor to the mitigation targets of the *Plano ABC* (MAPA, 2012). By integrating crop, livestock and/or forests in the same area, IS increases soil fertility and organic matter content (GIL ET AL. 2015a; BUNGENSTAB 2012). This not only increases carbon sequestration potential of the soil, but also allows for a higher stocking ratio, which reduces land demand (STRASSBURG ET AL. 2014), and allows for higher forage quality and a shorter time to slaughter, thus reducing lifetime enteric fermentation emissions (SMITH et al., 2014).

A variety of configurations exist for IS using either annual and/or perennial crops, and with varying field operations, planting densities and frequency of rotation between crops. This variation at the farm level means that mitigation potential of IS can only be assessed with precision at high resolutions (at the local level), and that national or regional aggregated values can be misleading (GIL ET AL. 2015a). In 2013, there were about 1.6 Mha under some form of IS in Brazil (BALBINO ET AL. 2011). There are high potential productivity gains associated with IS implementation. The Santa Brigida farm study by EMBRAPA (OLIVEIRA et al., 2013) in the state of Goiás, produced a meat yield increase from ~30 kg/ha to about 240 kg/ha, allowing for a rise in the stocking rate from 0,5 AU/ha in 2006 to 2.5 AU/ha during the fattening phase (60 days), and even to 4.8 AU/ha in the procreation phase (120 days).

IS in Brazil has been implemented using crops such as soybeans, maize, rice, millet, oats and sorghum (ZIMMER ET AL. 2012; MACEDO ET AL. 2014). Given its high biomass yield, Eucalyptus is the main species used in the forestry component of IS in Brazil, which also implies high carbon sequestration potential. The Plano ABC abatement target of 18-22 MtCO2eq on 4 million hectares of land implies a specific sequestration potential of 4.5-5.5 tCO2eq/ha. DE ALMEIDA ET AL. (2013) estimate mitigation of about 18 tCO2eq/ha is possible with an iCLF system that includes 220-350 eucalyptus trees per hectare harvested at 8-12 years of age and yielding 25 m3 of wood per hectare. In addition, the use of legume species capable of biological nitrogen fixation has the added benefit of potentially reducing demand for fossil-based nitrogen fertilizers (BARCELLOS ET AL. 2008).

Three types of IS were implemented in BLUES, following three implementations presented in SENAR (2013):

1. Crop-livestock rotations with maize (*CL1*) over 10 years, in which maize is planted on 1/3 of the area for part of the year, producing forage for the livestock (known as the *Santa Fe* system).
2. Crop-livestock integration with maize and soybeans (*CL2*) rotated over 10 years on ¾ of the area (¼ maize, ½ soy), with pasture area doubling during the dry season as it takes over the area just planted with maize.
3. Crop-livestock-forest (*CLF*) IS in which eucalyptus is planted in rows, averaging 20% of the area over a period of 20 years.

Animal units associated with all three schemes was set at 2.5 AU/ha, which is the predominant stocking rate throughout the long duration periods of these schema. The yields for the three co-products (maize, soy and wood) were adjusted to reflect the yields implemented in the crop production module of the model, coming from IBGE (2017a). Table 3-21 shows the resulting yields for the 3 schema for each of the regions in BLUES.

Table 3-21 – Yields of the co-products in the three schemes of integrated systems modelled in BLUES (Unit = t/ha)

Region	CL1			CL2			CLF		
	Maize	Soy	Wood	Maize	Soy	Wood	Maize	Soy	Wood
NO	3.06	0	0	4.00	2.94	0	0.55	0.31	2.73
NE	2.02	0	0	2.65	2.91	0	0.37	0.30	2.73
SE	6.15	0	0	8.05	2.90	0	1.11	0.30	2.73
SO	6.82	0	0	8.92	2.96	0	1.23	0.31	2.73
CW	5.32	0	0	6.96	3.07	0	0.96	0.32	2.73

Source: prepared by the author, based on SENAR (2013)

SENAR (2013) also provides the costs associated with the three schemes. These are shown in Table 3-22, including the cost of buying calves as described in Section 3.3.6.1.

Table 3-22 – Benchmark costs of the integrated crop-livestock schema modelled in BLUES

Bovine_Meat	**Cattle_Meat_LoCap**	**572**	**536**	**574**	**636**	**577**
	Cattle_Meat_HiCap	787	765	821	967	758
	Cattle_Meat_IntSys	894	870	916	1010	859
Bovine_Milk	Cattle_Milk_LoCap	877	789	523	364	638
	Cattle_Milk_HiCap	741	667	442	308	539
	Cattle_Milk_IntSys	842	759	493	322	611

3.3.8 GHG emissions from agriculture

Agricultural activity is associated with different levels of GHG emissions, and the processes in BLUES are assigned emissions factors (EFs) associated with a unit of activity for the given process. As discussed before, AFOLU emission factors are highly uncertain, and IPCC Tier 1 default values are usually applied because there is not enough knowledge about the processes governing land use to allow for a reliable estimate for national Tier 2 emission factors (GofB, 2015a). Therefore, top-down estimates of these factors were included in BLUES unless more accurate information was available at the time. As explained before, recent studies have started to understand the specifics of land use emissions for Brazil. For the livestock sector, CARDOSO et al. (2016) published results of field studies that allow for the calculation of Tier 2 factors. When the land use module was implemented, the question at hand was to which extent could intensification of livestock production spare enough land to accommodate the high levels of biofuels (with and without CCS) that were being deployed in the solutions of the COPPE-MSB energy system model. In particular, the focus of the effort was to look into potential for recuperation of degraded pastures. Hence, the first implementation had a more detailed livestock sector, and we turn to that first before moving on to crop production in the following section.

In the first version (used in Case Study 1 below), nitrogen application was not modelled explicitly. For crop production N_2O emissions, the model's first implementation used top-down estimates for AFOLU emissions that used Tier 1 default EFs derived from application of default IPCC methodology (IPCC, 2006c). Subsequent improvements (Case Study 2) added Tier 2 EFs to crop cultivation where possible using values found in the literature. Especially, additional effort was made to use Tier 2 values for the variables that were perceived as central to the analyses being conducted.

3.3.8.1 Livestock inputs and GHG emission factors

Parameters for livestock production were implemented using results from studies found in the literature. In particular, one recent study CARDOSO et al. (2016) provided detailed estimates of required inputs and GHG emission factors that were empirically derived for five scenarios of livestock production intensity. The details provided in the article contained enough information to populate the variables linked to the inputs used, the resulting output productivity, and GHG emissions of the two basic levels of grazing intensity that were implemented in BLUES, namely, the low- and high- capacity pastures.

Low-capacity pasture parameters were selected from Scenario 1 in CARDOSO et al. (2016), while the high-capacity pastures in BLUES used those from Scenario 4. The relevant parameters drawn from that study are summarized in Table 3-23. As described before, low-capacity pastures are characterized by minimal management, and infrequent (if at all) renewal of the pasture, with virtually zero fertilization post formation. These characteristics are reflected in scenario 1 in CARDOSO et al. (2016). According to that scenario, it is assumed that no diesel or urea are used in low-capacity pastures. CH_4 EFs are high due to poor forage causing longer time to slaughter and higher enteric fermentation rates. N_2O EFs are low since no nitrogen is added[25].

Table 3-23 – Values of selected parameters implemented in BLUES

	Low-cap pastures	High-cap pastures	Unit
Management	Degraded *Brachiaria* pasture Limed and fertilized at planting only Never renewed No mineral salt lick No documentation No breeding control	Guinea grass (*Panicum maximum*) cv Tanzânia Lime + PK fertilizer added at planting Urea added at 150 Kg/ha.yr Renewed every 5 years with Carbonate and PK fertilization Good documentation and breeding control	
Diesel use	0	6.5	L/ha
Urea use	0	144.7	kg/ha
CH4 EF	77.2	41.9	kgCH4/head
N2O EF	0.237	1.26	kgN2O/head

Source: adapted from CARDOSO et al. (2016)

On the other hand, high-capacity pastures used parameters from Scenario 4 from CARDOSO et al. (2016). As can be seen, the use of both diesel and urea (N-fertilization) increase from low-capacity to high-capacity pastures. This enables increased productivity and lower CH_4 EFs for high-capacity pastures since higher quality pastures also decrease the CH_4 intensity

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[25] As noted before, only direct emissions from AFOLU are accounted for in BLUES as of this writing.

of the product meat via better quality feed and shorter time to slaughter (Section 3.3.2.3), both of which drive down lifetime CH_4 emissions of the animals (ASSAD et al., 2015; SMITH et al., 2014).

N_2O EFs, on the other hand, increase more than threefold in high-capacity pastures, driven by nitrogen application in the form of urea. Although urea demand was not modelled explicitly in the first version, the resulting emissions from nitrogen application were included in the EF. In mitigation scenarios, the trade-offs between methane and N_2O emissions, as well as the costs and direct emissions of urea and diesel demand, are central to model decision to switch from low- to high-capacity pastures. It is important to note that the first implementation of the land use module included only CH_4 emissions from livestock, but not the respective N_2O emissions.

3.3.8.2 Crop cultivation inputs and N_2O emission factors

In the first version of BLUES, nitrogen application was not modelled explicitly, and N_2O emissions were included as an emission factor derived exogenously. Uniform emission factors were implemented as the same value for all crops in all regions. The value was set at 0.0007 tN_2O/ha using a top-down approach that simply divided total N fertilizer application by total crop production, as reported by FAO (FAO, 2018) for the year 2010. Working backwards from there and using the default IPCC N_2O emission factor of 1% of applied N, implies a 70 kg/ha uniform agricultural N_2O emission factor across crops and livestock.

Although this is an obvious over-simplification, the results derived from this version in Case Study 1 (Section 4.2) provided important insights into the potential for livestock intensification to spare land for food and energy crop production. Since the livestock sector was the main target of analysis, a top-down approach for N_2O emission factors was assumed adequate for a first case study. This first case study helped to identify the next priorities for model development, namely, to explicitly model nitrogen application rates. Nitrogen application is the main source of N_2O emissions playing a significant part in constraining energy crop development in scenarios with high carbon prices. A subsequent version of BLUES including nitrogen application was then used to test the sensitivity of the results to the choice of agricultural N_2O emission factor as described in Case Study 2 (Section 4.2).

Given the very local nature of agricultural practices, different methods of aggregation to national, regional, or global levels generate much uncertainty and variation. Moreover, the larger the aggregation region, the higher the uncertainties to be expected. Thus, a very large country with high variability in agricultural practices and/or edaphoclimatic conditions (like Brazil e.g.) is bound to harbor great variability in the emission factors of agricultural activity. Hence, in such cases, and whenever possible, Tier 2 methodology is preferred. As will be explained below, recent research suggests actual N_2O-N emission factors specific for Brazil from fertilizer application may differ significantly from default Tier 1 value of 1% suggested by IPCC national inventory guidelines.

The next sections describe the implementation of nitrogen application in BLUES.

3.3.8.3 Nitrogen fertilizers and N_2O emission factors in BLUES

Nitrogen fertilizer demand by crops is implemented in BLUES as an input parameter in the form a utilization factor per hectare in the crop production process. The N_2O emissions resulting from this N application is calculated via an EF as described in the next section.

Nitrogen application is converted to urea-equivalent in order to tie its use to the chemical industry sector and fertilizer imports. This is important to drive either production or importation of nitrogen compounds at both an energy and a financial cost. Urea production is modelled as a process requiring industrial steam, heat and mechanical drive. These inputs in turn are modelled as the outputs of processes that take as input(s) the energy carrier(s) which would deliver the least costly product. This depends on not just the cost of the input energy carrier, but also on the efficiency with which it delivers the desired commodities. The cost of urea production derives from the combination of these processes and is highly dependent on the price of the input energy carriers (natural gas e.g.), which is endogenously defined by the model. On the other hand, the cost of importing urea is set at US$300 per ton, which reflects an approximate average of international prices for the past 10 years[26].

3.3.8.3.1 Implementing nitrogen use in agriculture in BLUES

Nitrogen fertilization is a fundamental practice in modern agriculture, and it is done via synthetic and organic fertilizers, manure and crop residues left in the fields. All these practices lead to direct N_2O emissions via enhanced nitrification and denitrification rates, as well as through indirect routes such as leaching and volatilization (IPCC, 2006c). Direct nitrogen application from fertilizers and nitrogen from residues left on fields are both included in BLUES. Estimating indirect routes of N_2O emissions is beyond the scope of this thesis and is left for later research. In the present work, only direct routes were considered in order to increase transparency and simplicity. Indirect routes are subject to enormous

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[26] https://www.indexmundi.com/commodities/?commodity=urea&months=120

uncertainty and are also, in the case of volatilization and deposition, subject to long-distance air transport of N-containing molecules which may have been emitted by power plants and biomass combustion (IPCC, 2006c) in the first place, which is already counted in the energy sectors of BLUES.

Nitrogen application rates for crops and livestock production were taken from the ANUALPEC (2013) and AGRIANUAL (2013) datasets, which report on application rates on a per hectare basis of urea, ammonium sulfate and ammonium nitrate, and these were averaged and used as the parameters in BLUES. As described before, the N content of each of these compounds was converted to the urea equivalent unit by cross-multiplication of the N content of each.

Only a small portion of this applied N becomes N_2O. The default value used by the IPCC is 1% (IPCC, 2006b; SMITH et al., 2014). This value, however has been contested for tropical regions. In a study conducted specifically to estimate N_2O emission factors from agricultural soils in Brazil, ALVES et al. (2010) conducted a metanalysis of existing field studies that measured actual nitrous oxide emissions in various regions of Brazil, in soils under various crops, and for different seasons. The literature survey found an average emission factor of 0.32 across studies for the major agricultural crops in Brazil. This is an area of ongoing research and an effort is underway to determine appropriate national nitrous oxide emission factor from agricultural soils, so that new data should be available in the coming years, so that this value is likely to be updated. However, as the study by ALVES et al. (2010) is the most comprehensive publicly available survey of the existing literature for Brazil, this value was chosen as the baseline emission factor for agricultural N_2O in BLUES, applied to all crops in all regions. Future research should test the implementation of crop-specific and region-specific emission factors, based on existing and future published results of field experiments.

This approach follows a Tier 2 methodology for N use, since it uses available crop-specific data for N application rates and emission factors defined specifically for the country. On the other hand, the amount of agricultural residue left in fields is much less documented, and subject to local practices that can vary at the farm level, and for which there is no reliable data available. Thus, the parameter values in BLUES for residues left in fields used the emissions data reported in Brazil’s *3rd National Communication to the UNFCCC* (GofB, 2015a), which estimated N_2O emissions from agricultural residues for six major crops plus all others aggregated into an Others category. As explained in the *3rd Communication*, for permanent crops (coffee, oranges etc), no reliable data existed for the fraction of residues left on the field, so a default Tier 1 approach was used.

For the six major temporary crops (soy, sugarcane, beans, maize, rice, and cassava), the *3rd Communication* reported that a literature review was performed to elicit nitrogen left on the field as residues and, where no better data was available, default Tier 1 IPCC factors were used. The other crops in BLUES were mapped to the Others category of the *3rd Communication*. These values for nitrogen left on field from the *3rd Communication* were implemented in BLUES, so that the emission factors for this source of N_2O emissions still follows a Tier 1 approach. Once Tier 2 data becomes available, the current emission factors should be updated.

Table 3-24 shows the values implemented in BLUES for N use (in UREAeq units), the N_2O emission factors for each case of Tier 1 and Tier 2, and the resulting N_2O emissions per hectare for each crop in BLUES, including the double-cropped areas. It must be noted that these values result from the uniform implementation of nitrogen application data from AGRIANUAL (2013), which may not reflect average values in Brazil. A more thorough validation of these parameters needs to be undertaken. However, to ensure consistency of data used across all crops in the model diagnostics scenarios included in this thesis (Chapter 4), validation of nitrogen application rates is left for future research. This means that some of these values may deviate from reported data elsewhere.

Table 3-24 – Urea utilization factor and The Tier 2 N_2O emission factors (also include N from agricultural residues left on fields).

Crop	tUREAeq/ha	Tier 1 N_2O EF (%)	Tier 1 Emissions tN_2O/ha	Tier 2 N_2O EF (%)	Tier 2 Emissions tN_2O/ha
Wheat	0.122	1.0	0.000624	0.32	0.000200
Fruits	0.116	1.0	0.000505	0.32	0.000162
Soybeans	0.017	1.0	0.000798	0.32	0.000255
Maize	0.417	1.0	0.002608	0.32	0.000834
Cereal	0.073	1.0	0.000336	0.32	0.000108
Vegetables	0.348	1.0	0.000400	0.32	0.000128
Roots	0.127	1.0	0.000585	0.32	0.000187
Rice	0.256	1.0	0.001210	0.32	0.000387
Pulses	0.211	1.0	0.000970	0.32	0.000310
Oilseed	0.066	1.0	0.000224	0.32	0.000072
Nuts	0.226	1.0	0.001040	0.32	0.000333
Sugarcane	0.344	1.0	0.000764	0.32	0.000245
Coffee	0.994	1.0	0.004573	0.32	0.001463
Fiber	0.442	1.0	0.002032	0.32	0.000650
Grassy	0.073	1.0	0.000336	0.32	0.000108
Woody	0.435	1.0	0.002000	0.32	0.000640
Soybeans_Maize	0.083	1.0	0.001403	0.32	0.000449
Soybeans_Wheat	0.126	1.0	0.000779	0.32	0.000249

Source: Built by the author with data from AGRIANUAL (2013) and Alves et al. (2010)

It is worth noting that, although there nitrogen application may cause increases in CO_2 emissions from soils (CARMO et al., 2013), these interactions are not (yet) modelled in BLUES, as they are complex and fraught with uncertainties. Therefore, it is left for future research as it is beyond the scope of this thesis.

3.3.8.4 Carbonate application for soil pH correction

In addition to nitrogen fertilizers diesel fuel for, agricultural machines, and electricity (the latter mainly for irrigation), Brazilian agriculture has relied on the use of calcium carbonate ($CaCO_3$) to correct for soil acidity. This is especially the case in the midwestern region where the *cerrado* low pH (below 5.0) was a barrier to large-scale agriculture until the 1970s (CARVALHO, 2018; EMBRAPA, n.d.). Carbonate addition to soils was modelled for all crops and for high-capacity livestock production systems, with the values applied per hectare taken from AGRIANUAL (2013). According to the *3rd Communication* (GofB, 2015a), for each kilogram of carbonate added to the soil, 0.44 kilogram is emitted as CO_2. This emission factor was then used to calculate the emission factor for CO_2 from carbonate application in BLUES.

Table 3-25 shows the calcium carbonate application rates and resulting CO_2 emissions for all crops categories in BLUES. Just like nitrogen application, carbonate application was an improvement to the early version of BLUES and is not included in the version used in Case Study 1.

Table 3-25 – Calcium carbonate application and resulting CO_2 emissions per crop in BLUES.

Crop	$CaCO_3$ added (t/ha)	CO_2 EF (t/ha)
Sugarcane	0.500	0.22
Soybeans	0.500	0.22
Maize	0.400	0.18
Rice	0.000	0.00
Wheat	0.500	0.22
Pulses	0.500	0.22
Banana	1.000	0.44
Orange	0.408	0.18
Coffee	1.489	0.66
Cotton	0.350	0.15
Fruits	0.704	0.31
Cereal	0.100	0.04
Vegetables	2.000	0.88
Roots	0.000	0.00
Pulses	0.000	0.00
Oilseed	2.000	0.88
Nuts	0.150	0.07
Woody	1.496	0.66
Grassy	0.100	0.04
Double cropping	0.500	0.22

It is worth noting that, although there are interactions between nitrogen and carbonate that may cause increases in CO_2 emissions from soils, these are not (yet) modelled in BLUES. These interactions are complex and fraught with uncertainties. Therefore, it is left for future research as it is beyond the scope of this thesis.

3.3.8.5 Options for non-CO2 emissions abatement in agriculture

There are several options for emissions abatement in agriculture. These include nitrification inhibitors, planting legume species to enhance biological nitrogen fixation, dietary oil supplement to reduce enteric fermentation of ruminants, and manure digesters for production of biogas from manure. These are important technological elements in mitigation scenarios that are missing from the current implementation of BLUES and this effort is left for future research. Available mitigation options were described in detail in SMITH et al. (2014). However, for a country as large and as diverse in edaphoclimatic terms as Brazil, the potential for these technologies needs to be assessed and the country-specific literature should be surveyed to ensure accurate parameter choices. Since the mitigation options in AFOLU are dominated by intensification and land sparing possibilities, it was decided that the technological mitigation options would be left for future research. Moreover, the options are not additive and some of them may actually cancel each other out partly (SMITH et al. 2014), so their implementation would be scenario dependent. This further complicates the analysis and reinforced the notion that it would be better addressed at a later point.

3.4. Up-to-date documentation for BLUES

This chapter presented the methodology used to construct the land use module in the BLUES model, as well as some of the results from applying this methodology which produced the values of some of the parameters implemented. Since this model will continue to be developed, the descriptions here will gradually become outdated. For up-to-date documentation, the reader is referred to the IAMC/ADVANCE wiki website at the following web address:

http://themasites.pbl.nl/models/advance/index.php/Model_Documentation_-_BLUES

We turn now to some examples of scenarios that apply the BLUES model to help answer some key questions about the nexus energy-climate-land use in Brazil. These scenarios were used to generate the case studies described in Chapter 4.

4. Case Studies

We next turn to the application of the BLUES model. As is the case with any modelling exercise involving future projections, a set of input assumptions guide the creation of scenarios aimed at exploring variables of interest. Chapter 2 included a brief summary of scenario analysis theory, which formed the basis for the construction of the scenarios used here. The main input assumptions and parameters used are described next.

The scenarios used in the present work were developed under the umbrella of the CD-LINKS project[27], a "research project that brings together a consortium of nineteen leading international research organizations from around the globe to explore national and global transformation strategies for climate change and their linkages to a range of sustainable development objectives." The scenarios were based on interactions between global integrated assessment models and national energy-environment systems models, where global models inform national models as to GHG emissions trajectories and carbon budgets consistent with Paris Agreement goals to keep average global temperature increases below 2^{o}C over pre-industrial era by the end of the century (http://cd-links.org/).

We turn now to the description of the scenarios used here, and how they derive from the CD-LINKS set of scenarios.

4.1. Basic Premises

The Reference scenario (*Ref* henceforth), is based on the NPi, or *Current Policies* scenario from CD-LINKS. This scenario adds to SSP2 base line by including key current policies implemented until 2015 which impact emissions in every region of global models and in Brazil in the case of BLUES. A list of the current climate policies implemented can be found in the Climate Policy Database[28] and are summarized in Table 4-1. This scenario has no explicit emissions constraints and is the baseline against which additional efforts to stay within the 1.5°C and 2°C temperature targets are measured, which are captured in the other scenarios.

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[27] http://cd-links.org/

[28] ttp://www.climatepolicydatabase.org/, accessed May 2017.

Table 4-1 - Policies implemented in the Current Policies scenario and all scenarios derived from it.

Scenario	**Policy**	**Measure**	**Implementation**	**Period**
Current Policies (*Ref*)	Biofuel blending	Ethanol blending into gasoline	27.5% by volume	start 2010
		Biodiesel blending into fossil diesel	7% (B7) 10% (B10)	start 2010 start 2019
	Low-carbon Agriculture (ABC) Plan	Degraded pasture recuperation	15 Mha	2015-2025
		Integrated systems	4 Mha	
		Planted forests	3 Mha	
	Electricity	Power plants under construction or licensed in 2015	--	2010-2020
	Ban on incandescent light bulbs	Substitution by CFLs and LEDs	--	start 2020
	Deforestation	Net-zero by 2030	--	start 2030

Source: compiled by the author for CD-LINKS project. For detailed descriptions of each policy, see the CD-LINKS climate policy database (http://www.cd-links.org/?p=681)

4.1.1. Carbon budgets

To assess climate change mitigation pathways, two other scenarios were developed based on the Ref scenario, but using different cumulative carbon emissions constraints, consistent with the 2 °C and 1.5 °C targets of the Paris Agreement, respectively. As explained before (Section 2.3), these so-called carbon budgets were introduced so as to take effect starting in 2020, and thus models follow the *Ref* trajectory through 2020 and then optimize the system to stay within the allowed carbon emissions budget for the whole period 2010-2050. However, because GHG concentrations in the atmosphere are global in nature, it only makes sense to speak of global carbon budgets. Hence, the contribution of any one country (Brazil in this case) has to be derived in a globally consistent manner, from models that somehow allocate the global budget to each region.

There are several criteria based on which one can allocate a global carbon budget to the regions, including criteria of fairness, cost, capacity or historical emissions (HÖHNE et al., 2014; PAN et al., 2017). The scenarios used in these case studies are the product of global cost-minimization model runs which allocate emissions reductions to the regions so as to minimize the global cost of achieving a given budget. This means that the possibility exists that regions may be allocated an emissions budget that is different than what would be the regional optimal solutions. Rather, the global total cost is optimized. Other criteria such as fairness are not included in the allocation scheme. The application of an emissions budget based on criteria other than global cost-minimization is left for future research.

The budget scenarios described here are therefore the result of applying country-level carbon budgets for Brazil emerging from global mitigation scenarios consistent with Paris Agreement goals by imposing on the Ref scenario budgets consistent with:

- *2deg* scenario: >66% chance of staying within a 2 °C target (with a global 2011-2100 carbon budget of 1000 GtCO2), and
- *1p5deg* scenario: >66% chance of staying within a 1.5 °C target (with a 400 GtCO2 global carbon budget).

The emissions budgets implemented into BLUES were derived from the results for the Brazil region from global runs of the COFFEE model (ROCHEDO, 2016). Table 4-2 shows the mean and median of the resulting budgets for Brazil in each scenario across models participating in CD-LINKS having Brazil as a separate region, along with the COFFEE budget that was ultimately implemented in BLUES. It is worth noting that the budgets mean and median from the other models were skewed downwards by outliers with negative budgets for the 2010-2050 period, something we find not to be a feasible alternative[29]. Without these outliers, the COFFEE budgets are very close to both the mean and median of the remaining values.

Table 4-2 - Brazil CO_2 budgets 2010-2050. Mean and median from global models participating in CD-LINKS project, with Brazil as a separate region. COFFEE budget was implemented to national model BLUES (in $GtCO_2$)

Scenario Name	Baseline scenario	Global Budget	Mean	Median	COFFEE
Ref	Current Policies	-	28.8	29.7	-
2deg		1000	14.6	20.5	23.6
1p5deg		400	7.3	11.3	15.4

Global models included in the calculations for Brazil budget mean and median values are: IMAGE, AIM/CGE, DNE21+, GEM-E3, POLES and GCAM

It must be noted that, although one speaks of "carbon" budgets, these are in reality CO_2-only budgets. This is because they reflect cumulative concentrations, and therefore cannot be applied to transient or short-lived species of GHGs, such as methane or nitrous oxide, which

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[29] By negative budgets it is meant that Brazil's cumulative 2010-2050 emissions should be negative, an unlikely proposition. As a test for the limits of mitigation in the BLUES model, I ran a scenario with infinite carbon cost (around $1 million per ton of CO_2), and the resulting budget was around 4.4 Gt CO_2 by 2050. Thus, in my view, values too far below this level are not realistic for Brazil.

decay according to their half-lives in the atmosphere (IPCC, 2014). Since the half-life of methane is shorter than the 100-year study periods typical of IAMs, elaboration of GHG budgets is complex, since, for example, most of the methane emitted in the beginning of the period is already transformed into CO_2 by the end of the period (IPCC, 2014). Thus, non-CO_2 gases must be addressed in a different manner.

The budgets were implemented in BLUES as a maximum cumulative ceiling for CO_2 emissions and, to limit emissions of non-CO_2 GHGs, these were priced at their GWP100 value based on CO_2 prices that came out of the same COFFEE runs that generated the national CO_2 budgets for Brazil. The resulting prices attached to each gas are shown in Table 4-3.

Table 4-3 – Carbon prices for the three GHGs. CO_2 prices from the COFFEE runs that generated the CO_2 budgets. Non-CO_2 gases priced at their GWP100-AR4 conversion values. (Values in 2010US$)

Temp target	Global CO_2 Budget	Gas	GWP100-AR4	2010	2015	2020	2025	2030	2035	2040	2045	2050
2°C (>66% chance)	1000	CO_2	1	0	0	0	9	18	16	15	18	22
		CH_4	31	0	0	0	280	561	510	459	570	680
		N_2O	298	0	0	0	2694	5388	4902	4415	5476	6537
1.5°C	400	CO_2	1	0	0	0	11	22	21	19	32	45
		CH_4	31	0	0	0	346	691	642	593	999	1404
		N_2O	298	0	0	0	3321	6643	6171	5699	9600	13500

4.1.2. Macroeconomics

There is broad consensus that the Brazilian economy will continue to expand in the coming decades, as is expected of an emerging economy. However, there is much uncertainty as to how fast it will grow, that is, how high the GDP growth rate will be. Official projections by government institutions place it above 3% on annual average between 2010 and 2050. The Empresa de Pesquisa Energetica has made several indicative energy expansion plans in recent years with broad ranges of macroeconomic assumptions. In the *Plano Nacional de Energia 2050*, for example, it devised four different macroeconomic scenarios, with average annual growth rates for 2014-2050 ranging from 3.6% to 4.1%, low and high scenarios respectively (EPE, 2014a).

International institutions have also projected high growth rates for Brazilian GDP. Projections made for the Shared Socioeconomic Pathways (SSPs) have estimates for Brazilian GDP growth rates (DELLINK et al., 2015) as shown in Table 4-4. The central scenario described by SSP2 represents a middle of the road case for several socioeconomic pathways and can be used as a reference scenario that includes a mix of business-as-usual socioeconomic development, as explained in Section 2.2 (O'NEILL et al., 2013). For the scenarios in this thesis, SSP2 was used as the starting point, but corrections to short-term GDP growth (pre-2020) were made as explained next.

Table 4-4 – Brazilian GDP growth rates estimates derived from absolute values available in the SSPs database. Units = %

	2010-2015	2015-2020	2020-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050
SSP1	3.3	4.5	4.4	4.1	3.8	3.5	3.0	2.6
SSP2	3.3	3.7	2.8	2.4	2.3	2.1	1.9	1.8
SSP3	3.3	3.4	2.1	1.5	1.2	1.0	0.7	0.5
SSP4	3.3	3.6	2.5	2.2	2.0	1.8	1.6	1.4
SSP5	3.3	4.8	4.9	4.6	4.3	3.9	3.4	3.0

Data source: © SSP Database (Version 0.9.3) https://secure.iiasa.ac.at/web-apps/ene/SSPDB

Although the foregoing high growth rates might have been reasonable to expect a few years ago, recent developments caused a marked reduction in economic activity in Brazil that has made such estimates obsolete. The average growth rate for the period 2011-2015 was just 1.5% per year (ADVFN, 2015). The most recent estimates published by the Brazilian Central Bank indicate Brazilian GDP shrinking by 3.81% in 2015, shrinking again by 3.54% in 2016, and returning to modest growth in subsequent years (BCB, 2016). These recent and projected growth rates are combined to construct Table 4-6.

Table 4-5 – Historic and projected Brazilian GDP growth rates (%).

2011	2012	2013	2014	2015	2016	2017	2018	2019
2.7	0.9	2.3	0.1	-3.81	-3.54	1.14	1.69	1.96

Sources: 2011-2014 historic: ADVFN (2015); 2015-2019: BCB (2016)

In order to create realistic GDP projections for Brazil, we adjust SSP2 growth rates (Table 4-4) by replacing average growth rates for the periods 2010-2015 and 2015-2020 by average historic and projected rates derived from Table 4-5. The resulting projection is shown in Table 4-6, which translates to an annual average of 1.9% for the whole period 2010-2050.

Table 4-6 – Adjusted Brazilian GDP annual growth rates

2010-2015	2015-2020	2020-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050
1.5%	0.3%	2.8%	2.4%	2.3%	2.1%	1.9%	1.8%

Source: built by the author with data from IIASA and BCB (see text)

These short-term changes affect the long-term performance of the Brazilian economy even if subsequent GDP growth rates are maintained as shown in Figure 4-1. This, in turn, will affect future demand for agricultural commodities which are projected based on GDP growth rates and value-added projections for the key sectors, as described next. Thus, it is important to make the correction for the short-term fall in GDP.

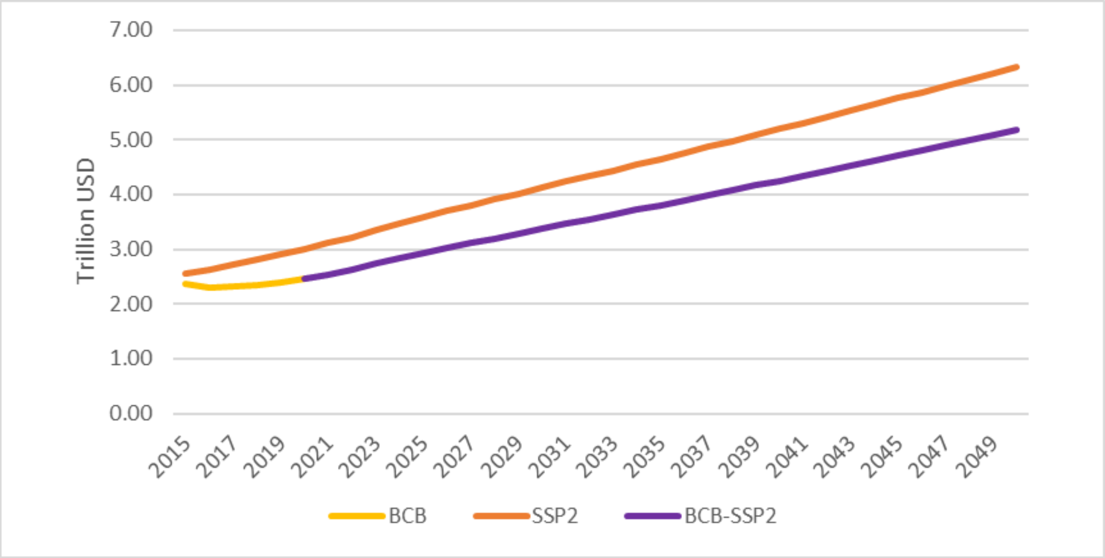

Figure 4-1 – Comparison of GDP growth rates as projected for SSP2 (DELLINK et al., 2015) to short-term corrections based on BCB (2016), for the period pre-2020 and following implied growth rates from SSP2 thereafter (see text)

Demand projections in the scenarios in this thesis were developed by applying this corrected SSP2-BCB projection for Brazilian GDP growth rates to the economic structure in SZKLO et al. (2017). Table 4-7 shows the resulting demand projections for the agricultural commodities modelled in BLUES.

Table 4-7 - Agricultural demand in CD-LINKS scenarios

Product (kt)	2010	2015	2020	2025	2030	2035	2040	2045	2050
Wheat	6171	6855	7107	7824	8551	9248	9861	10345	10730
Fruits	38833	42178	43458	47445	51651	55810	59554	62581	65017
Soybeans	34116	37572	39281	42687	46567	50611	54335	57333	59696
Maize	51714	56398	58570	63901	69787	75816	81382	85987	89763
Cereal	1938	2120	2192	2400	2618	2831	3023	3178	3303
Vegetables	8923	9968	9953	11022	11925	12633	13183	13595	13954
Roots	29010	30694	31046	33523	36077	38537	40698	42413	43768
Rice	11236	12122	12377	13549	14744	15888	16895	17698	18339
Pulses	3172	3397	3464	3764	4075	4376	4644	4860	5034
Oilseed	196	210	213	233	253	271	287	299	310
Nuts	1422	1491	1496	1614	1730	1837	1929	2001	2057
Coffee	2312	2554	2676	2914	3185	3468	3729	3939	4106
Fiber	3244	3454	3516	3798	4099	4394	4657	4867	5033
Sugar	29969	31901	30511	32376	32338	32130	31762	31320	30991
Maize Oil	81	85	86	93	100	106	112	116	120
Soybean Oil	6928	7322	7000	7487	7455	7395	7310	7215	7146
Other Oil	1911	2015	2027	2192	2355	2508	2639	2742	2823
Bovine Meat	9326	9867	9981	10777	11598	12389	13083	13635	14071
Other Meat	10733	11407	11605	12547	13547	14531	15410	16119	16687
Butter	92	97	99	107	116	123	130	136	140
Eggs	1984	2098	2116	2291	2464	2625	2764	2873	2960
Milk	2686	2817	2825	3048	3268	3471	3644	3779	3885

4.1.3. Other restrictions

In order to capture other specific realities of the Brazilian case, the scenarios also introduce constraints to the model that include limits on land use transitions, electric vehicle penetrations, and biofuel export rates. For land use, an assumption of net-zero deforestation post-2030 was implemented. In the energy sector, the price of electric vehicles was assumed to reach parity with conventional internal combustion engine vehicles by 2040, a trend that may prove conservative given recent developments in the sector (BNEF, 2017). In order to ensure consistency with international trade levels, constraints on the amount of biofuels that can be exported were set based on values obtained for Brazil from the same COFFEE runs that generated the carbon budget values. In other words, the global model COFFEE sets the bounds applied to the national model BLUES. These include oil producers' prices, as well as international trade of energy and crop commodities. For instance, these were applied to diesel and kerosene exports, which the model was exporting in excess in order to capture CO_2 via the BTL-with-CCS and ATJ routes available to produce these biofuels.

4.1.4 Differences between the model versions used in the Case Studies

As mentioned before, there were differences in the model version used in each case study. The main difference is the modelling of nitrogen application in crop production which for Case Study 2 was modelled explicitly, while the model version used for Case Study 1 had a top-down average value for N_2O emission factor across all crops and regions. In addition, carbonate application for soil pH correction (Section 3.3.8.4) was not included in the Case Study 1 version but added to the version used to generate the Case Study 2 scenarios.

Another difference that is important to mention is that in the early version (Case Study 1), the methane emission factors used for livestock did not vary regionally. Rather, a single average emission factor was used across all regions and across all cost classes. This causes CH_4 emissions to be under-represented in the results. This was a simplified first attempt to measure the impact of livestock intensification on GHG emissions in Brazil, as well as on energy system development. Given the significant impacts of livestock intensification on both emissions and energy system configuration, BLUES was updated for Case Study 2, so that i) CH_4 emission factors for livestock are regionalized and vary across cost classes as described in Section 3.3.8.1, and ii) methane emission factors also account for indirect emissions from livestock as described in Section 3.3.8.1. This is reflected in the total cumulative emissions for the period 2010-2050 as will be seen in the final chapter of this thesis.

4.2 Case Study 1: Transportation biofuels and land use change

As mentioned before, the interlinkages between biofuels and land use dynamics is of central interest to this thesis. In this case study, an application of the scenarios described in the previous section allows for the exploration of these interlinkages. In addition, the electrification of transportation in Brazil and worldwide could reduce demand for biofuels, especially by light-duty-vehicles (LDVs). This, however, does not imply a reduction in the demand for biofuels. Rather, unused biofuels used in LDVs could be further processed into higher value-added products such as drop-in bio-jetfuel and biodiesel, which would maintain pressure on the AFOLU sectors to produce biofuels. This dynamic interplay between the AFOLU and the energy sectors responds to varying degrees of GHG emission restrictions.

This case study was the first exercise using the newly implemented BLUES model and was part of the EU-funded CD-LINKS project. Part of these results were recently submitted as a journal article to a special issue of *Climatic Change*[30]. It is important to emphasize that this case study uses an early version of the model, prior to the implementation of fertilizer use in crop production. Thus, the results presented in this case study derived from scenarios that assumed uniform N_2O emission factors from different crops. The value was set at 0.0007 tN_2O/ha, a value found using a top-down approach that simply divided total N fertilizer use by total harvested area, as reported by FAO (FAO, 2018) for Brazil in the year 2010. Working backwards from there and using the default IPCC N_2O emission factor of 0.1% of applied N, implies a 70 kg/ha uniform emission factor for N_2O-N. The next case study will explore the sensitivity of the results obtained in this one to the choice of agricultural N_2O emission factor. For that case, a more recent version of the model was used in which N application was modelled explicitly.

4.2.1 Results

In general, results indicate the interlinkages between AFOLU and the energy sectors is of central importance to ensure the viability of the mitigation scenarios. This suggest trade-offs between land-based mitigation and biofuels production may present challenges. Results also confirm the fundamental role played by AFOLU in Brazil's mitigation efforts, with the sector contributing to zero Brazilian emissions before the energy sector. The intensification of livestock appears as a particularly attractive option to reduce emissions from livestock, but also to spare land for the production of food, feed, fiber and biofuels. Nonetheless, it will be shown that even a stark transition to higher capacity pasture is not enough to prevent further conversion of natural lands to agriculture through deforestation. Crop production also intensifies, with increases in double-cropped areas and integrated systems.

In the energy sector, besides biofuels, a shift to renewables in power generation occurs alongside bioelectricity deployment. In the budget scenarios, technological shifts occur to further decarbonize sectors with remaining mitigation potential. In the energy sector, the model deploys low-carbon energy sources for all energy carriers, fuel switch in transportation, energy efficiency in industry, as well as transitions to low carbon power generation options like biomass (mostly bagasse), wind and solar.

The transportation sector stands out as having significant potential for emissions abatement through biofuels, with and without CCS, and electrification of the LDV fleet for passenger

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[30] Submitted on 01 Nov 2017 as "Brazil emissions trajectories in a well-below 2ºC world: the role of disruptive technologies versus land-based mitigation in an already low-emission energy system". Authors: Alexandre C. Köberle, Pedro Rochedo, Andre F.P Lucena, Alexandre Szklo, Roberto Schaeffer

transportation. In the tighter budget scenarios, introduction of electric vehicles (EVs) leads to increases in electricity demand, affecting expansion strategies for power generation, while changes in the mix of biofuels affect the agricultural sector.

4.2.1.1 GHG Emissions

Figure 4-2 shows the GHG emissions trajectories of the three scenarios analyzed. As GHG emissions become increasingly constrained, CO_2 emissions are drastically reduced and eventually turn negative. While emissions of non-CO_2 gases are also reduced, they decrease at a slower rate than CO_2 emissions, so that by mid-century an even larger share of GHG in Brazil will come from nonCO_2 species.

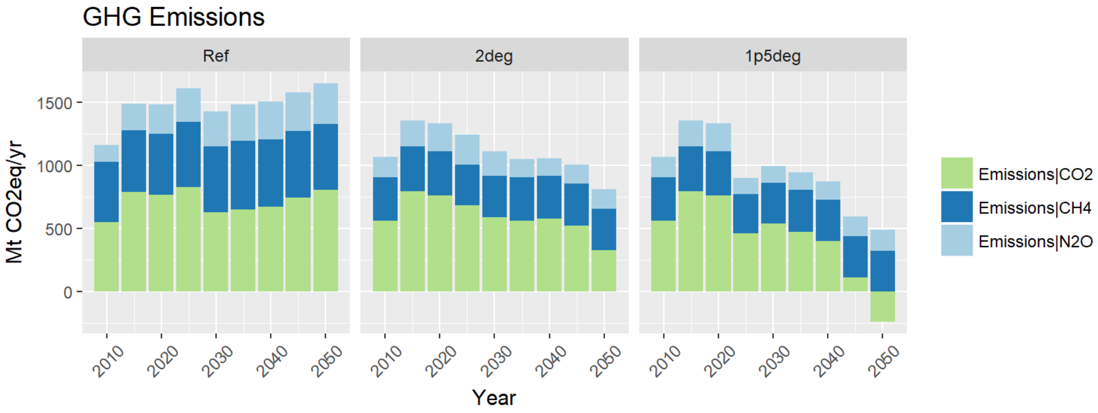

Figure 4-2 – GHG emissions trajectories in BLUES

Methane emissions do not change much, while nitrous oxide emissions are significantly abated in both mitigation scenarios. As we shall see in the next sections, this is a due to a combination of factors involving intensification of agricultural practices being partially offset by increase in demand for agricultural products.

4.2.1.2 Land use and land use change

As noted, AFOLU sectors are central to Brazil's mitigation effort, and this is reflected correctly in the model results. Changes in land use in the different scenarios are shown in Figure 4-3. Intensification of livestock means that large areas are converted from low-capacity pasture into high-capacity pasture, which have average stocking rates twice as high. This holds across all scenarios, including the reference scenario, where a reversal of the increasing trend of low-capacity pastures indicates this is an attractive measure even in the absence of climate policies. Intensification of crop production also occurs, evidenced by the increase of double-cropped and integrated systems areas, and a shift to higher yield production of sugarcane in single-cropped areas.

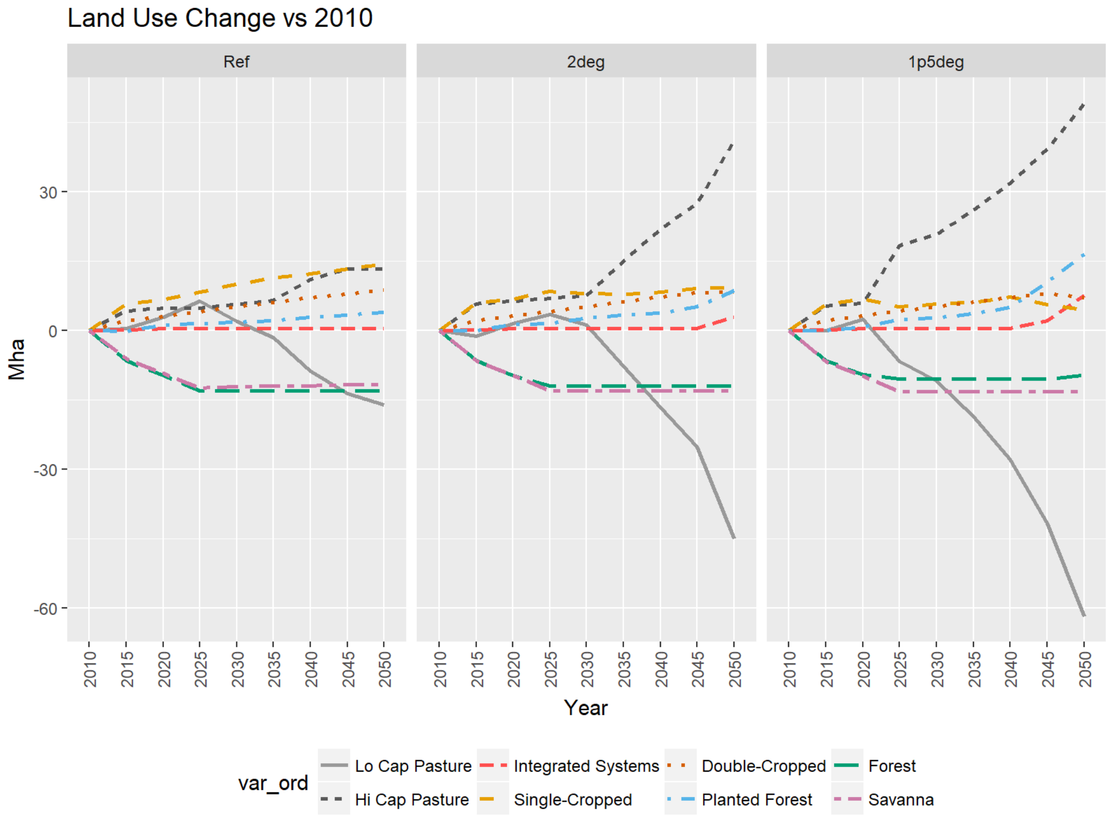

Figure 4-3 – Land cover change versus 2010

The general trend across scenarios is for continuing conversion of natural land to agriculture. Figure 4-3 shows the area change in 2050 relative to 2010 for each land cover type displayed in in BLUES. According to these results, further conversion of between 22.9 and 25.4 Mha of natural lands may be needed to meet demand for food, fiber and energy, depending on the scenario. In the current policies scenario (*Ref*), natural land conversion stops after a peak around 2025. As the budgets become more stringent, forests are allowed to recover more and savannas less. This is because forests represent higher carbon stock and yield more CO_2 sequestration per unit area than savannas. However, it is not a zero-sum game. Comparing *Ref* to the other scenarios, in most cases there is a reduction in natural lands and an expansion in cultivated lands. The only exception for this occurs in the *1p5deg* scenario, that is, in the scenario representing a 1.5°C target, where a 3.3 Mha increase in forest cover is accompanied by a 1.6 Mha reduction in savanna area, with a net gain of 1.7 Mha of natural land coming from reduction in cultivated area (Table 4-8).

Table 4-8- Land cover change in 2050 relative to 2010 – negative values mean reductions in area (Mha)

Scenario	Cropland	Double Cropped	Forest Planted	Lo Cap Pasture	Hi Cap Pasture	Integrated System	Forest	Savanna
Ref	13.3	8.5	3.9	-13.9	12.3	0.4	-13.0	-11.6
2deg	6.6	8.8	6.7	-49.8	48.4	4.0	-11.6	-13.1
1p5deg	4.6	7.0	16.5	-61.7	49.0	7.5	-9.7	-13.2

4.2.1.3 Primary energy

Primary energy consumption (PEC) is expected to grow in Brazil in the coming decades, driven mostly by population growth and income rise (EPE, 2014b). This is clearly reflected in the *Ref* scenario, which shows increases in all currently-used energy sources (Figure 4-4). In the mitigation scenarios, biomass increasingly replaces oil and coal as emissions constraints become tighter. In the most stringent case of *1p5deg*, coal virtually disappears, oil use drops by as much as 50%, and biomass share grows to around 50% of total PEC by 2050. This significantly increases land demand for bioenergy production and helps explain some of the land use dynamics described in Section 4.2.1.1.

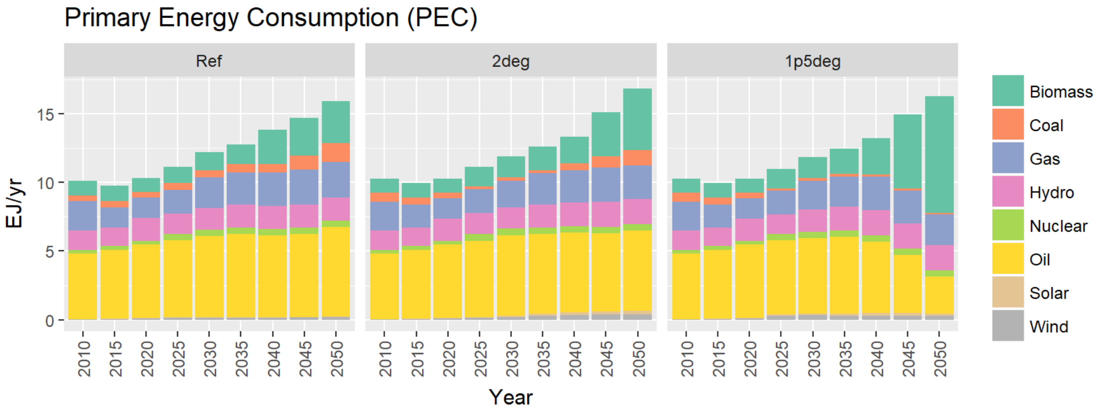

Figure 4-4 – Primary Energy Consumption (PEC) in Brazil across scenarios

4.2.1.4 Power generation

Hydropower remains the mainstay of the Brazilian electricity system, but its share of production decreases in all scenarios (Figure 4-5), including the reference. This is not surprising since the hydro potential is expected to become saturated in Brazil, with the exception of areas in the Amazon, where developing that potential would require transmission across large distances and would likely face public opposition due to sensitivity of that biome. In the absence of climate policies (*Ref*), coal-fired generation gains space in this cost-optimization model, as it produces the lowest-cost electricity. This was also a feature of the previous versions of BLUES, namely MESAAGE-Brazil and COPPE-MSB, which showed coal power beginning to gain space after 2030 as the hydropower potential becomes saturated (LUCENA et al., 2015; PORTUGAL-PEREIRA et al., 2016). Nonetheless, wind, solar and nuclear generation also see significant increases. This happens already in the current policies scenario (*Ref*) and increases with growing stringency of the emissions budget.

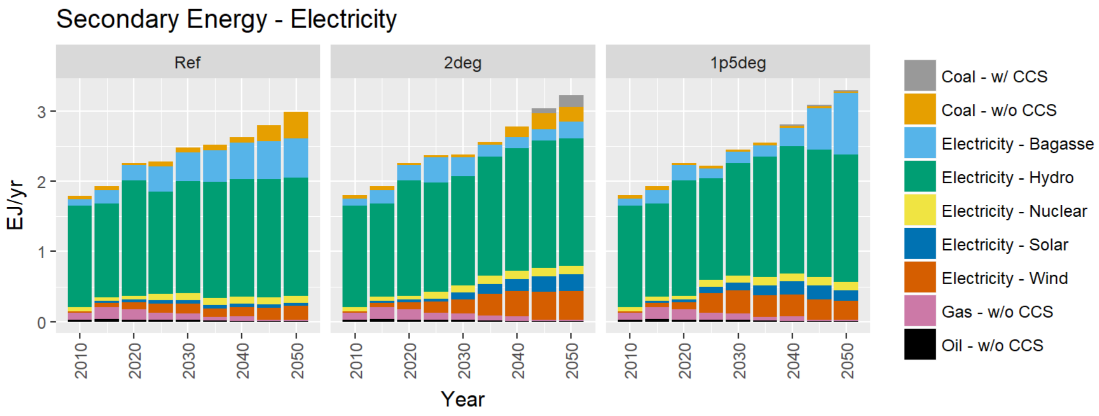

Figure 4-5 – Power generation in Brazil across scenarios

Hydro, solar and wind face competition from biomass-fired power generation

Counterintuitively, the *1p5deg* scenario shows lower deployment of wind power than the *2deg*. This is a result of the need for quick decarbonization post-2030 in the *1p5deg* scenario, which brings about high levels of BECCS deployment in bioliquids production, leading to large amounts of bagasse availability. The early deployment of low-carbon technologies in the mitigation scenarios leave more room for emissions in the post-2030 period, even permitting operation of coal-fired power plants well into 2050 in the less-stringent *2deg*. As would be expected, the *1p5deg* scenario deploys large amounts of biomass-fired power generation. There is also higher electricity demand in the mitigation scenarios, a result of electrification of the LDV (Section 4.2.1.5).

4.2.1.5 Biofuels

As emissions budgets tighten across scenarios, non-sequential changes happen in the biofuels sector (Figure 4-6). That is, there is no progressive deployment of a technology. Instead, a break occurs when going from the *2deg* to the *1p5deg*, meaning that the mix of biofuels produced in the former is very different than the mix in the latter, a potential pitfall of incrementalism in policy design in Brazil. Even so, Brazil is projected to produce large amounts of biofuels. In fact, results indicate that it will produce more than it consumes, becoming an exporter of high quality drop-in biofuels in the *1p5deg* scenario, especially of bio-jetfuel from alcohol-to-jet (ATJ) route. The ATJ route takes ethanol and turns it into drop-in bio-jetfuel (DE JONG et al., 2015), implemented as an add-on unit to existing ethanol distilleries (repurpose). The sharp increase in production in the *1p5deg* scenario is driven both by decarbonization of domestic aviation and by exports. To ensure global trade consistency, the ATJ export levels in BLUES were constrained to follow the amounts resulting from the global COFFEE runs for these same scenarios.

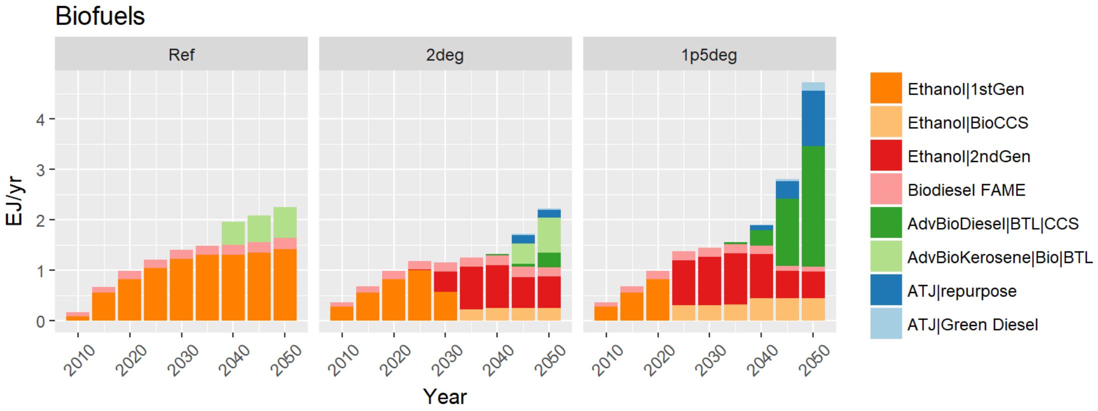

Figure 4-6 – Biofuels production deployed to meet energy services demand in Brazil

On the other hand, significant deployment of BTL-diesel with CCS helps decarbonize national freight transportation. Road transportation by diesel trucks is by far the most important modal for freight in Brazil (EPE, 2014c). BTL-diesel also becomes important for passenger transportation, allowing diesel engine buses to remain an important option even in the mitigation scenarios. Interestingly, BTL-biojet fuel enters the mix in the *Ref* scenario. The production of this BTL-biojet fuel happens in the North and Northeast sub-regions, and results from both the absence of refineries producing fossil jetfuel in these regions, and the abundance of zero-cost ligno-cellulosic residues from deforestation and from planted forests. In addition, the ATJ route also produces synthetic diesel as a coproduct (ATJ|Green Diesel), contributing to the supply of much needed low-carbon diesel fuel. Note that an ad-hoc assumption was made that all ATJ production uses 2nd generation ethanol (ligno-cellulosic) only. This is necessary because the technology is modelled as drawing from a common ethanol pool fed by all ethanol producers, so it is impossible to determine the origin of the ethanol ultimately used in the model by the ATJ repurpose route. Thus, 2nd generation ethanol production is much larger than it appears in the figure, which shows final use.

4.2.1.6 Transportation

For the transportation sector, decarbonization efforts result in higher use of biofuels with and without CCS, and (partial) electrification of the LDV fleet (Figure 4-7). Flex fuel vehicles remain the most important private passenger transportation alternative, running mostly on about 50% gasoline and 50% ethanol. Flex vehicles are modelled as operating in two modes: the ratio gasoline/ethanol is 30/70 in option 1, and 70/30 in option 2. Option 2 dominates in all scenarios modelled here, including *Ref*. Because Brazilian gasoline is blended with anhydrous ethanol at roughly 25% by volume (E75), average flex vehicle consumption is evenly split between gasoline and ethanol.

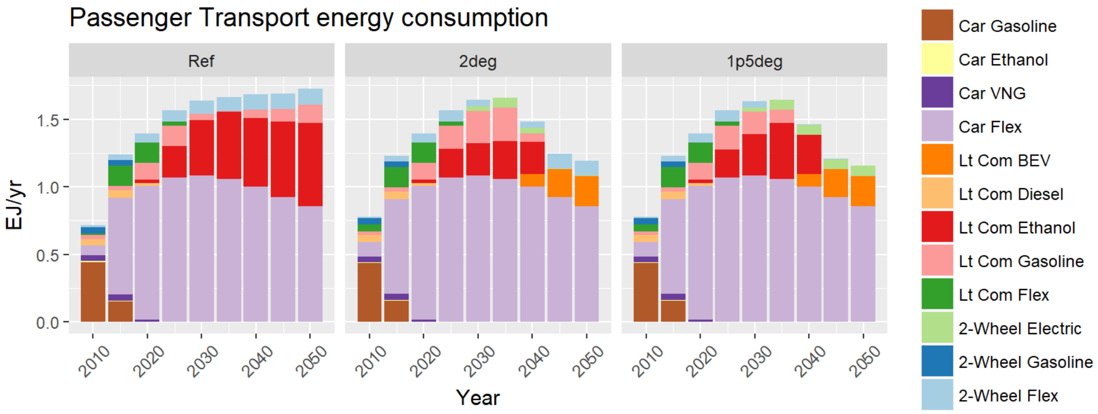

Figure 4-7 – Private passenger transportation technologies deployed to meet demand in Brazil

The mitigation scenarios show electrification of the LDV fleet beginning in 2035. In private passenger transportation, motorcycles and heavier passenger vehicles (named Light Commercial in the model) are substituted by their electric counterparts starting in 2035 (Figure 4-7). Because Evs have a higher conversion efficiency of the energy carrier (electricity) to motion than internal combustion engines (ICEs), this causes a significant drop in energy consumption to meet the same demand for passenger transportation services. As noted earlier, this results in increasing electricity demand, with implications for power generation (Section 4.2.1.3).

Although COPPE-MSB has higher efficiency options for all passenger public transportation technologies, the only one taken up by the model is more efficient airplanes in the *1p5deg* scenario. This change is solely responsible for the drop in energy demand for public passenger transportation that occurs as we go from the *2deg* to *1p5deg* scenario (Figure 4-8).

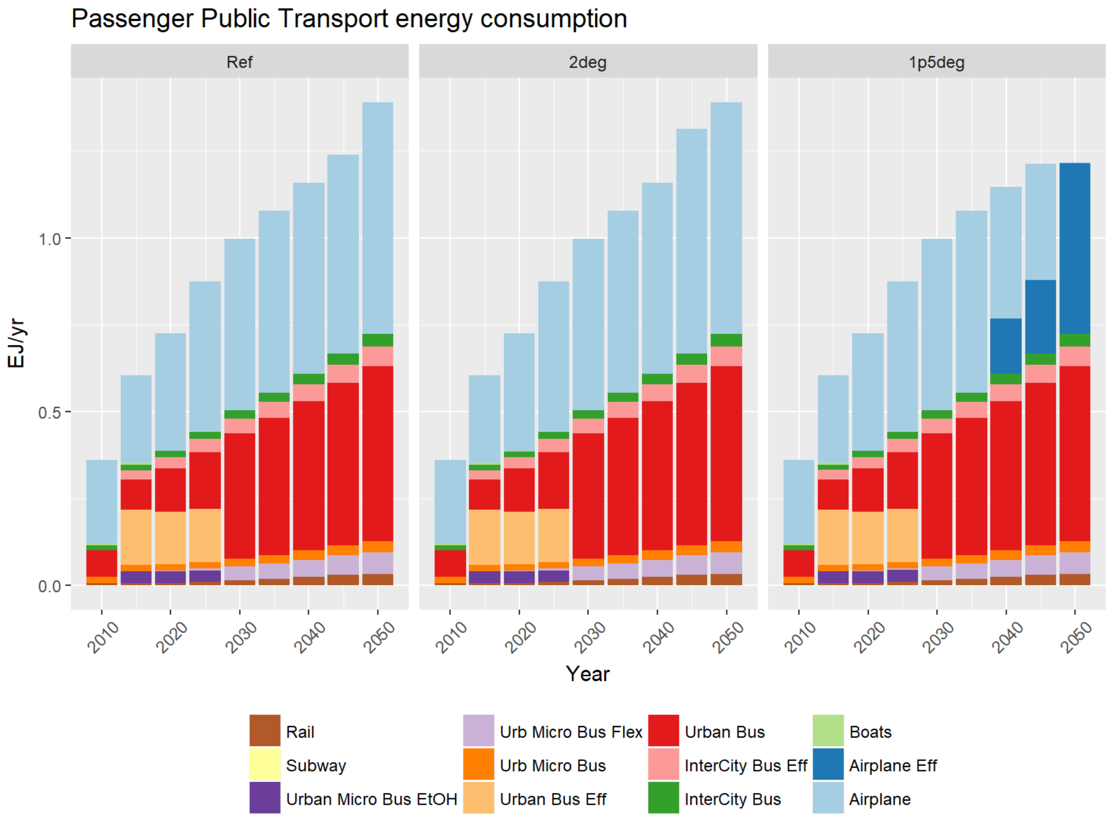

Figure 4-8 – Public passenger transportation technologies deployed to meet demand in Brazil

For the case of freight transportation, a couple efficient options are taken up, but this happens across all scenarios, even in the *Ref* (Figure 4-9), so no changes happen as we move to more stringent GHG emissions constraints.

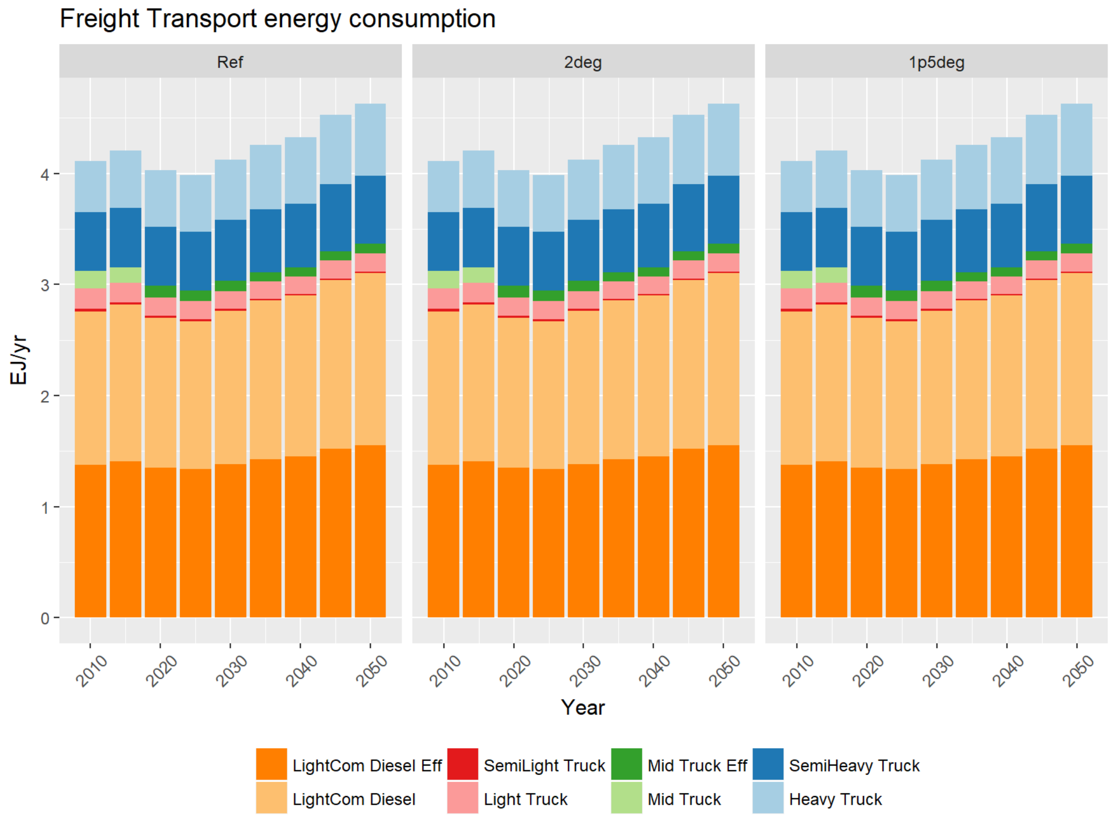

Figure 4-9 – Freight transportation technologies deployed to meet demand in Brazil

4.2.2 Discussion

The results shown above indicate potential interlinkages between the AFOLU and energy sector. Because of the already low-carbon power generation mix in Brazil and relatively few alternatives in industry, the transportation sector stands out as the main sector to be decarbonized as the country moves to higher ambition mitigation scenarios. The main driver behind the dynamics seen in biofuels production is the transportation sector. The electrification of the LDV fleet, combined with the lack of alternatives for decarbonization of freight and air transport, drives the shift from ethanol to advanced biodiesel and biokerosene.

As seen in the previous section, the composition freight transport does not change across scenarios. This is somewhat unsurprising given that the overwhelming majority of freight transport in Brazil occurs via diesel trucks over an inefficient network of roads, which is not expected to change in the short time horizon to 2050 to allow for advanced (and capital-intensive alternatives) like electric or hydrogen trucks. Hence, to reflect this reality in Brazil, the model does not have many options to decarbonize freight transportation.

Therefore, solutions private passenger transport and aviation adopt low-emissions alternatives to accommodate this relative lack of flexibility in freight. In the *2deg* scenario, production of biokerosene allows aviation to contribute to the overall mitigation effort. In the *1p5deg* scenario, efficient airplanes reduce demand for kerosene so that most of the lignocellulosic feedstock is used to produce advanced biodiesel through the biomass-to-liquids route with CCS. In addition, the efficient airplanes are powered by biokerosene produced via the ATJ route, so significant decarbonization of air travel occurs. The electrification of the LDV fleet also frees up ethanol from 1st and 2nd generation to be used as feedstock to the ATJ process, which, incidentally, also produces biodiesel as a byproduct, further helping to decarbonize freight transport.

In addition, production of ethanol and sugar produces bagasse as a byproduct of sugarcane crushing, which is burned to produce CO_2-neutral electricity. This further reduces the GHG intensity of electricity in the grid, which enables deployment of Evs that run on low carbon power, reducing the demand for liquid fuels. This in turn impacts the refining sector. These interlinkages are affected by the input assumptions in the model, so that these results must be interpreted with care. Nonetheless, it points to specific areas where well-designed policy can have positive impacts across sectors, reducing trade-offs and enhancing synergies. Indeed, in a carbon constrained world, the enormous bioenergy potential in Brazil is an opportunity even as penetration of electric vehicles increases. However, the negative impacts that could happen in the form of land use change must be controlled via effective regulation.

There are interesting options for AFOLU as well. In agriculture, intensification of livestock production is evidenced by the shift from low- to high-capacity pastures. This is an important result of the model, since it reflects a trend that is currently being trumpeted by the agricultural sector as a major potential for sustainability gains, especially for the vast Brazilian beef industry. For land use, meeting the 1.5°C target implies the possibility of afforestation in the second half of the century as more land is spared through intensification (and also because of a projected demographics transition after 2050). This suggests that meeting the more stringent Paris Agreement ambition may bring co-benefits to forest conservation, which in turn alleviates pressures on biodiversity (VISCONTI et al., 2016). This points to a potential synergy between the SDGs for Climate Action (SDG 7) and Life on Land (SDG 14). Again, however, well-designed policy and good governance will be essential ingredients towards a sustainable future for Brazilian AFOLU, especially in a scenario of high biofuels demand.

4.3 Case Study 2: AFOLU emissions, non-CO2 gases and N fertilizers

Nitrous oxide emissions from crop cultivation are directly linked to nitrogen application rates, which was not explicitly modelled in the first version of BLUES. Thus, the results presented in the first case study derived from scenarios that assumed uniform N_2O emission factors from different crops. The value was set at 0.0007 t N_2O/ha using a top-down approach that simply divided total N_2O emissions by total crop production, as reported by FAO (FAO, 2018) for the year 2010. Working backwards from there and using the default IPCC N_2O emission factor of 0.1% of applied N, implies a 70 kg/ha uniform application rate across crops and livestock.

As shown in Case Study 1, in the budget scenarios, this resulted in a loss of competitiveness of sugarcane versus lignocellulosic feedstocks, even though sugarcane can be used as a feedstock for both first and second generation ethanol, as well as bioelectricity. One of the possible reasons is that, in the scenario protocol, N_2O emissions are extremely costly, and may be driving the results. It is interesting then to test the sensitivity to the choice of N_2O emission factor of sugarcane share of bioenergy feedstock. In order to do so, it is necessary to implement more crop-specific emission factors, which means, in IPCC parlance, moving from a Tier 1 approach to a Tier 2 approach.

Section 3.3.8.3 described the implementation of fertilizer use in crop production and a sensitivity analysis of N_2O emission factor choice between Tier 1 and Tier 2. The Tier 2 values were derived from literature for Brazil based on recent published experimental results that suggest emission factors in Brazil (and the tropics in general) may be much lower than the IPCC default of 1% of applied N-fertilization. Because the main objective here is to test mitigation potential of bioenergy, the sensitivity analysis only varied the N_2O emission factors of crop production, while those from livestock and soil management were kept constant. As noted in Chapter 2, livestock emission factors were already done in a Tier 2 methodology following data reported in various articles, but mainly CARDOSO et al (2016).

4.3.1 Results: Impacts on the energy system

As will be shown in the following sections, not all energy variables are affected by a change in the agricultural N_2O emission factors. In fact, some do not change at all, indicating that the solutions for them are robust against these changes. However, most do change even if in small amounts. For example, primary biomass consumption (Section 4.3.1.1) increases as grassy biomass (modelled as elephant grass) outcompetes sugarcane, under the scenario of cost reduction assumptions of 2nd generation ethanol production technologies that are built into BLUES. This causes changes in the biofuels mix that is produced in the country (Section 4.3.1.4). On the other hand, the power generation mix (Section 4.3.1.1) does not change so much. This does not come as a big surprise, given the low-carbon profile of Brazilian power generation, dominated as it is by hydropower. The contribution of bioelectricity from bagasse is maintained even though sugarcane production drops towards the end of the period, substituted by elephant grass (Section 4.3.2).

Such dynamics show that the choice of emission factor for non-CO_2 gases is important in future scenarios of (bio)energy production and use in Brazil, at least for the case of agricultural N_2O as shown here. The following sections delve deeper into the results.

4.3.1.1 Primary Energy

In the *1p5deg* scenario, the mix of primary energy consumption (PEC) is affected mostly through an increase in primary biomass use (+1.4 EJ/yr in 2050, modelled as elephant grass) and a concomitant drop in primary sugarcane (-0.26 EJ/yr). Primary oil consumption also drops (-0.3 EJ/yr) as biofuels become more competitive in the mitigation scenarios (Figure 4-10). All other variables remain roughly at the same level, which reinforces the idea that the main routes of influence follow the biofuels path, which replace more oil under lower agricultural N_2O emission factors.

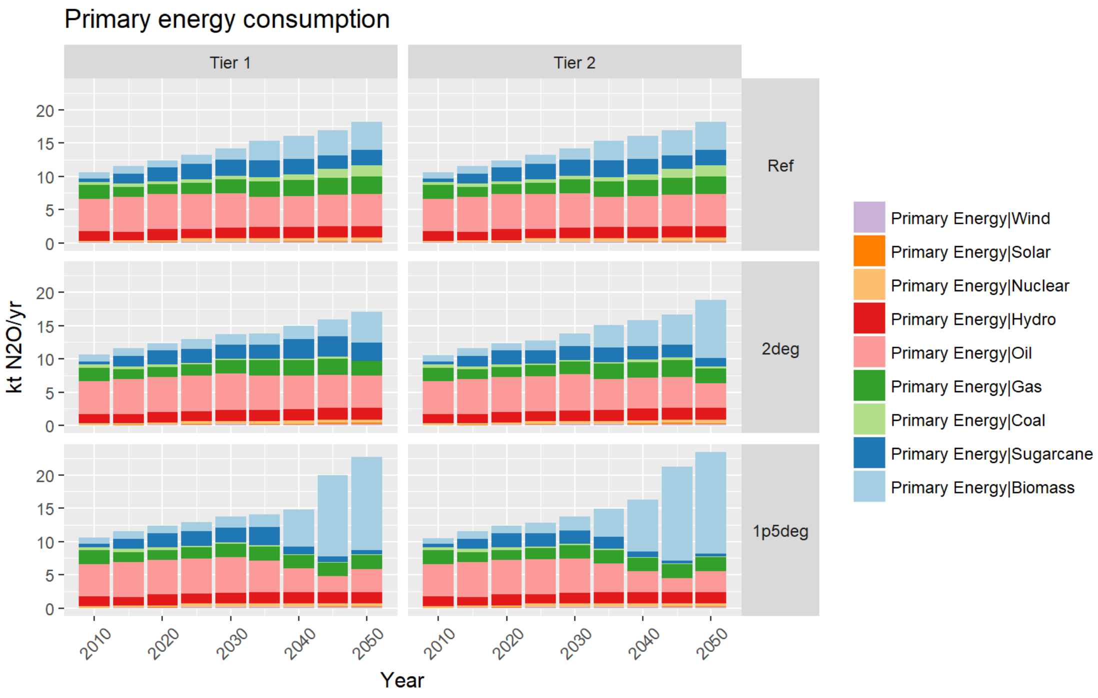

Figure 4-10 – Primary energy consumption by source across scenarios and Tier cases

4.3.1.2 Power generation

As mentioned before, power generation (Figure 4-11) does not change appreciably in Tier 2 scenarios, indicating robustness of the solution with respect to N_2O Efs. The main difference between the two cases happens in the *2deg* scenario, in which a relatively small drop in bagasse-fired generation in Tier 2 is replaced by coal without CCS post-2030. In the *1p5deg* scenario, this drop in bagasse is rather replaced by hydropower and a small drop in electricity demand, indicating energy efficiency measures.

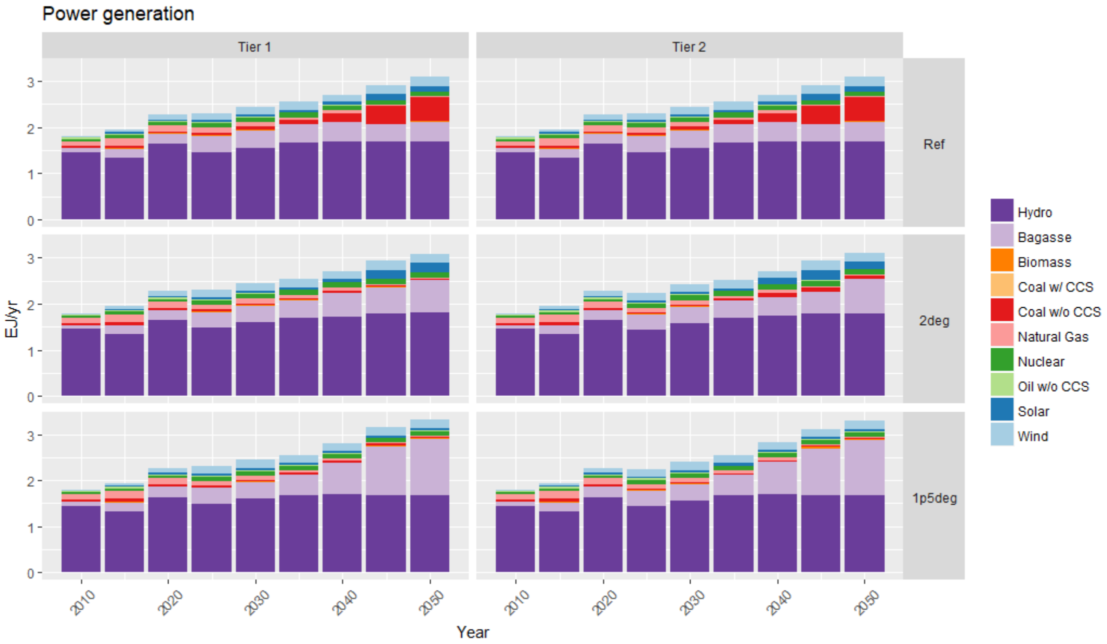

Figure 4-11 – Power generation across scenarios and Tier cases.

4.3.1.3 Transportation

There are no visible changes in either passenger or freight transportation options in the solutions, suggesting the solutions are robust with respect to agricultural N_2O emission factors. Solutions in the transportation sector are much more driven by competition between the different technologies, even as the biofuel mix in Brazil changes.

4.3.1.4 Biofuels

Biofuels production is the variable that most changes with the agricultural N_2O emission factors, as shown in Figure 4-12. It is interesting to note that the total demand for biofuels did not change, but the composition of the biofuels mix deployed to meet that demand did. Of particular note is the shift from ATJ route for biojet fuel production to advanced biokerosene routes using BTL technologies. There is also a shift from ethanol from 2nd-generation routes and with BECCS to a more balanced mix of 1st- and 2nd generation, and BECCS ethanol in the *1p5deg* scenario.

What drives these changes is not any alteration in the transportation sector fleet technologies per se, since the solution for both passenger and freight transportation deploys the same mix of vehicles in the Tier 1 and 2 cases. What changes is sugarcane competitiveness against elephant grass as both become less N_2O-emissions-intensive in Tier 2. Because the sugarcane chain has to deal with the vinasse residue, which generates a lot of N_2O emissions from field fertirrigation, elephant grass 2nd-generation ethanol becomes the preferred choice in the strict mitigation scenarios where N_2O emissions are priced at the highest level of the non-CO_2 gases modelled in BLUES. Of course, given the high uncertainties in N_2O emission factors from crop cultivation, a lot of care must be taken in interpreting these results. In fact, given that these two parameters, namely N_2O emission factors for sugarcane and elephant grass, drive the shift from one to the other, a thorough sensitivity analysis should be performed on these parameters to better analyze inflection points along the gradient of cross-competitiveness before making policy-relevant recommendations.

Figure 4-12 – Biofuels production across scenarios and agricultural N_2O emission factor Tier levels

4.3.2 Results: Impacts on agriculture and land use

4.3.2.1 Agriculture production

The shifts in biofuel feedstocks has an impact on the crops with connections to the energy system, namely sugarcane, soybeans and lignocellulosic biomass (Grassy and Woody). Figure 4-13 shows the production of these crops across the three scenarios, under each case of Tier 1 and Tier 2. Comparison of the two columns reveals that elephant grass (Grassy) production increases in Tier 2, indicating it has become much more competitive as shown by production increases of roughly 100% and 20% in the in the *2deg* and *1p5deg* scenarios respectively. This rise is accompanied by a reduction in sugarcane production in Tier 2 relative to Tier 1 cases across mitigation scenarios. In Tier 2 case it never breaks the 800 Mt annual production mark, not much higher than current production levels of about 600 Mt/yr, before dropping below 400 Mt in the *2deg* scenario and to about 550 Mt in the *1p5deg* scenario.

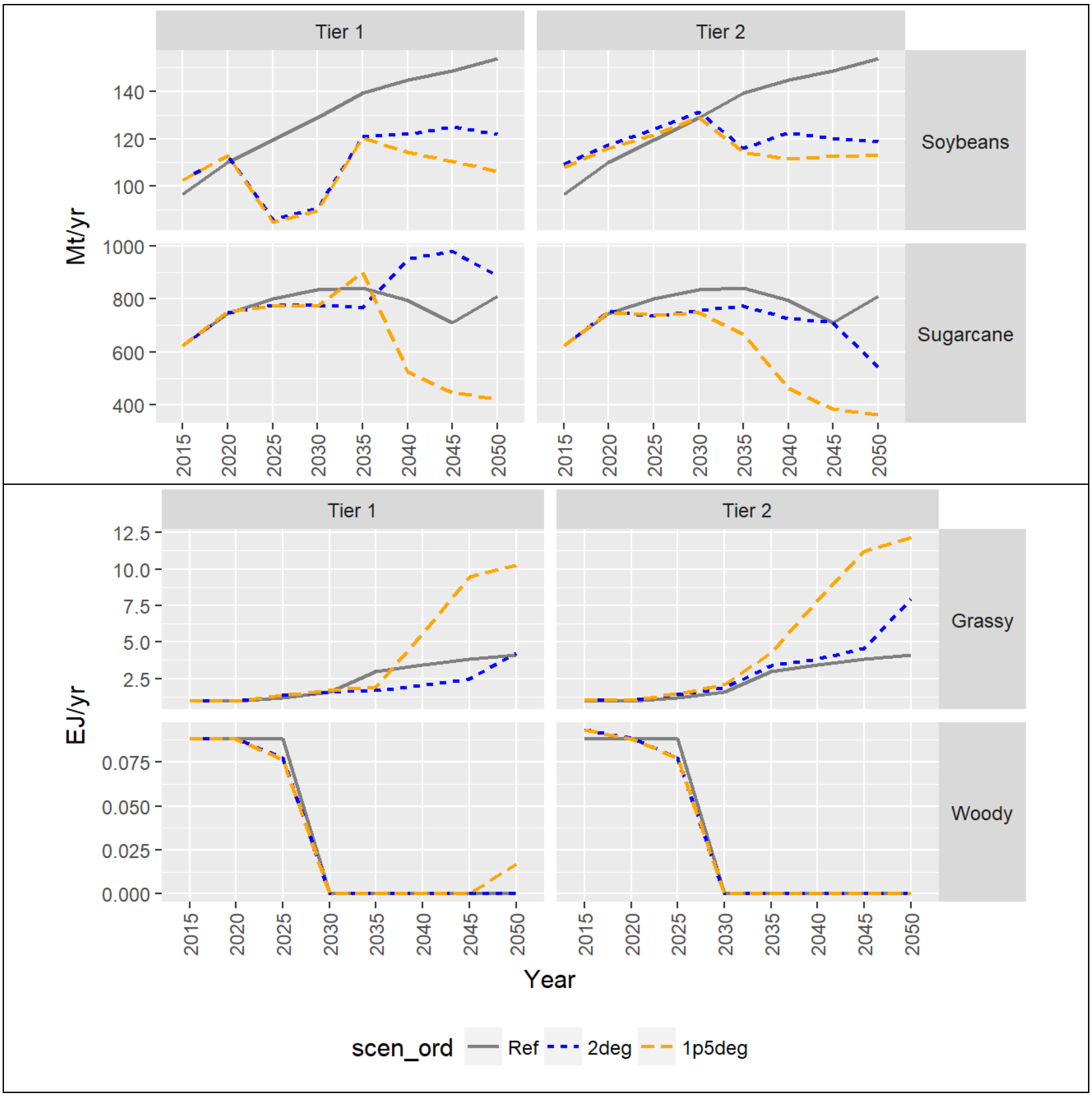

Figure 4-13 – Production of soybeans, sugarcane (top in Mt/yr), and Grassy and Woody biomass (bottom in EJ/yr).
Woody also includes agroforestry residues use as bioenergy feedstock in EJ/yr.

In contrast, soybeans production changes much less dramatically, remaining somewhere in the vicinity of 110 to 120 Mt/yr. Woody biomass is strongly affected by the availability of considerable forestry residue in the near-term, which abruptly falls to zero once the constraint for net-zero deforestation kicks in. This indicates, that all of the Woody biomass used by the model was in fact deforestation residue, except for the small increase in *1p5deg*/Tier 1 in the last time step of the run.

4.3.2.2 Land use change

The changes in bioenergy feedstock production impact land use patterns (Figure 4-14). Before embarking on a description of the results, it is important to remember that they are the result of input assumptions on demand for agricultural products and their relative costs. For example, food demand being purely exogenous, it is not elastic to rising agricultural commodity prices so it does not change in the mitigation scenarios in response to implied rises in the cost of carbon emissions associated with agricultural production. Also, the assumption of net-zero deforestation after 2030 is not guaranteed by Brazilian legislation. In its absence, the model would choose to continue deforesting rather than to make the investments necessary for the productivity gains reflected in these results. Finally, the solutions here are the result of total system cost minimization that do not necessarily mean each sector pursues its optimal solution. Nonetheless, even all these caveats, some lessons can be drawn from these results.

First, there are virtually no changes in the area of Other Land, which basically denotes the *Cerrado* biome in Brazil, which consistently bears the brunt of rising agricultural demand, be it for food production or bioenergy. With increasing stringency of the CO2 budget, more land conversion occurs in this land class to accommodate bioenergy feedstock production. The robustness of this results across scenarios and cases means the *Cerrado* biome should become a focus of environmental protection if the land, water and biodiversity resources found there are not to be lost. And although in the *2deg* scenario there is a recuperation of some of the area lost in the short-term for this land use class, this is reversed by the additional land requirements of meeting the *1p5deg* target.

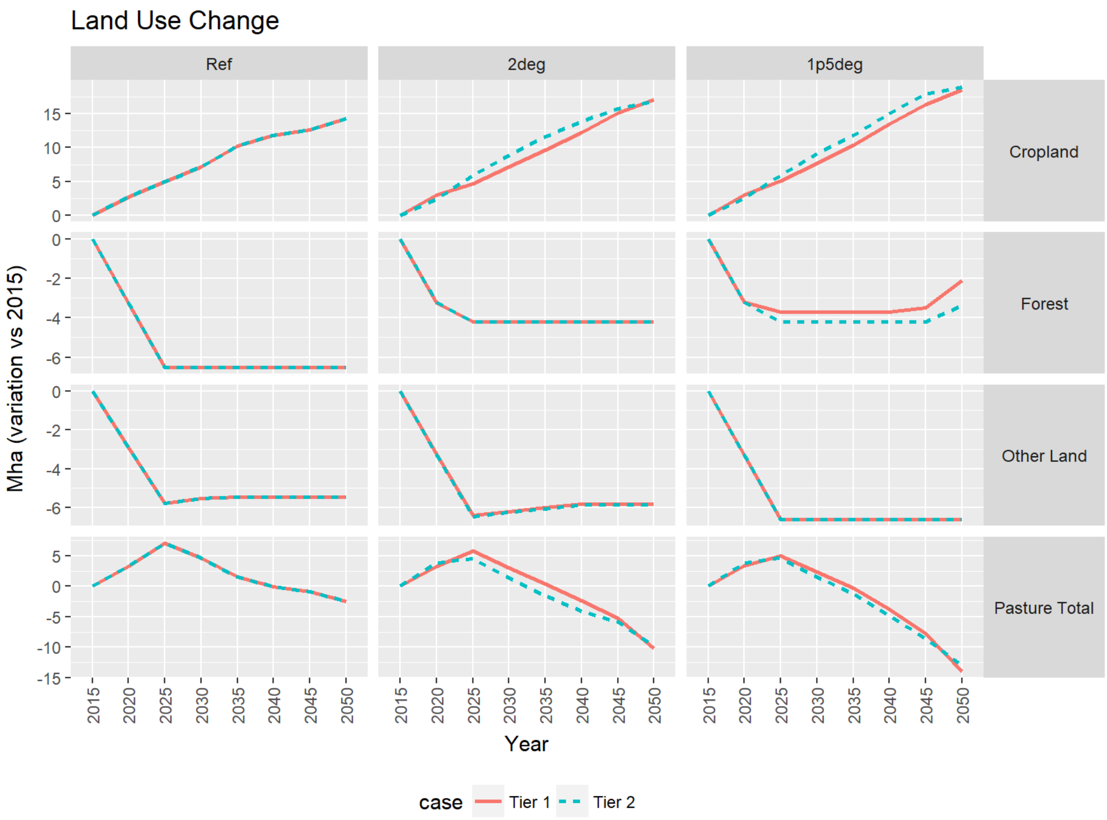

Figure 4-14 – Impact of agricultural N_2O emission factors on land use change across scenarios (Difference vs 2015; note different scales)

The other three dynamic land use classes modelled are differently affected by carbon budgets and choice of N_2O emission factor, although the direction of change across budget scenarios is maintained (Figure 4-14). In general, as carbon budgets become more restrictive, cropland and forest areas tend to increase while pasture and other land areas tend to decrease. However, there are differences in the magnitude of the changes across scenarios in each of the cases.

Cropland area increases more in both budget scenarios under Tier 2 than under Tier 1 in the medium-term but converges to the same area by 2050. Pastures show a similar pattern of medium-term divergence and convergence by 2050, with the difference that the 2050 area is much lower under Tier 2 scenario than under Tier 1, in the vicinity of 2.5 to 3 Mha less depending on the scenario. Smaller N_2O emission factors for crop cultivation also mean less mitigation potential, so that livestock sector mitigation options through intensification become more attractive in that, although they mitigate a smaller amount of N_2O emissions per hectare, they also have the added benefit of mitigating some CH_4, and at a smaller cost than in crop production.

Forest area shows no difference across tier choices in 2deg, but Tier 2 brings more forest loss under 1p5deg due to increased land demand of bioenergy feedstock productions.

4.3.3 Results: N fertilizers and Urea demand

As explained in Section 3.3.8.3, Nitrogen application is the variable upon which the N_2O emission factor acts to determine a crop's N_2O emissions intensity. As such, it does not change from Tier 1 to Tier 2. However, because there are shifts in choices across i) crops produced and ii) management levels within crops, N-application rates will also vary as we move from Tier 1 case to Tier 2, since different crops and/or management levels have different N demand. Urea was implemented in BLUES as the proxy N fertilizer.

Figure 4-15 shows the variation in national N demand in urea-equivalent units. There is marked increase in N demand, indicating a shift to crops that are more N-dependent (at least as far as the N consumption factors adopted from the literature indicated). This has impacts on other sustainability indicators, especially water quality, since agricultural N runoff is a major source of algal blooms that cause apoxya through higher biological oxygen demand (BOD). This is a negative trade-off from climate mitigation on improving water quality, one of the Sustainable Development Goals of the 2030 Agenda adopted by the UN in 2015. Thus, N-application rates can be used as a proxy for impacts of climate mitigation on water quality in scenarios implemented in BLUES. However, even better would be an estimate of Nitrogen released to the environment, which can be done through a coefficient not very differently than it is done for N_2O emissions. Tier 1 N leaching factors from IPCC equal 0.30 (IPCC, 2006c). Although more country specific factors would be preferable, as of the time of this writing, there are no Tier 2 estimates.

The reduction in the first time-step is a result of the GDP reductions caused by the economic crisis in Brazil, and the assumed effects that has on domestic demand for agricultural products.

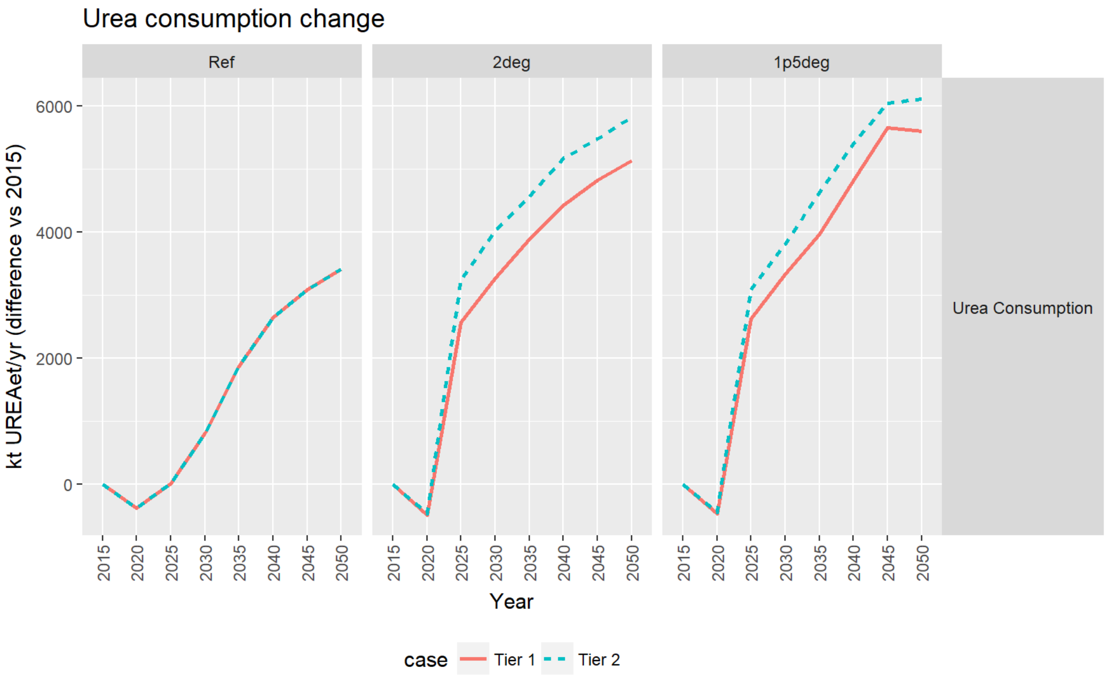

Figure 4-15 – Nitrogen consumption variation vs 2015 in urea-eq units

4.3.4 Results: GHG emissions

The Brazilian GHG emissions is slightly altered by the adoption of Tier 2 emission factors for agricultural N_2O. Naturally, N_2O emissions are reduced with Tier 2 implementation of N_2O emission factors for crops cultivation, since the new emission factors are consistently lower than the default Tier 1 values previously used.

4.3.4.1 Nitrous oxide

Nitrous oxide emissions are (naturally) those most affected by the new choice of emission factor. Although there is considerable difference between Tier 1 and Tier 2 results, the relative mitigation effort across budget scenarios does not change appreciably as shown in Figure 4-16.

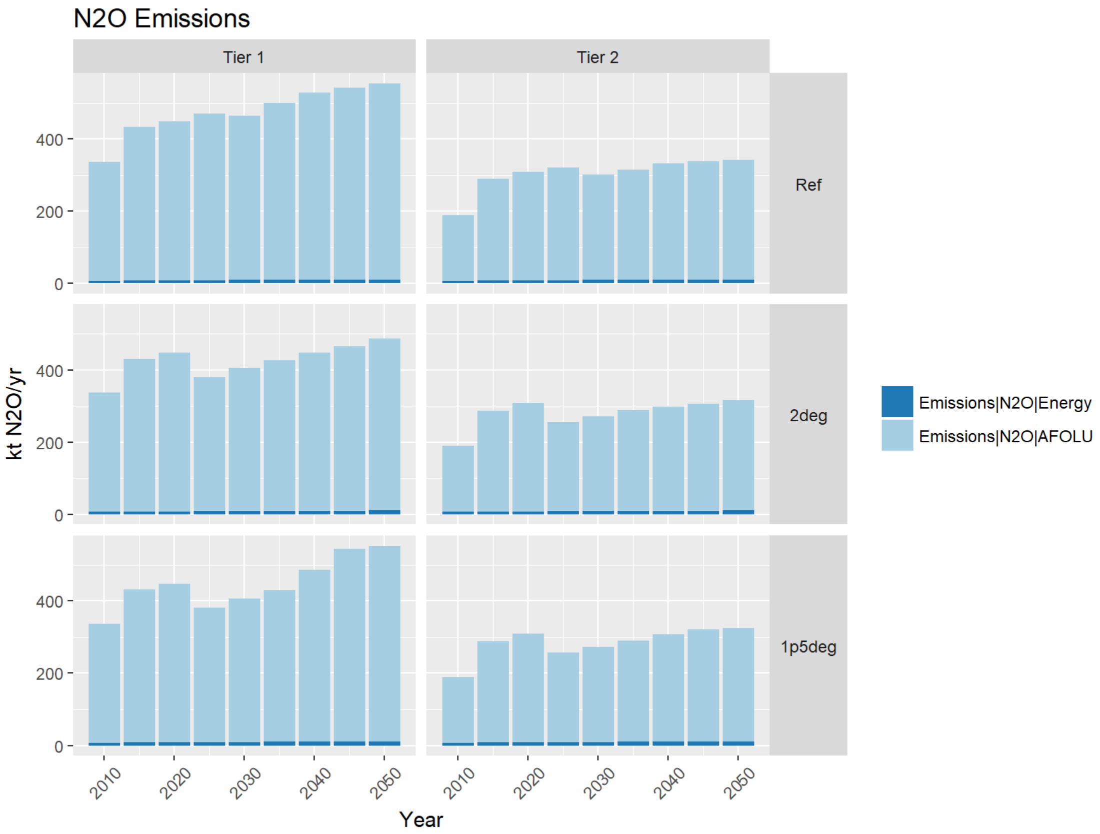

Figure 4-16 – N_2O emissions across scenarios and Tier cases

4.3.4.2 CO_2 emissions

CO_2 emissions are significantly affected by the choice of agricultural N_2O emission factors, through second order effects of agricultural practices on energy system variables, especially biofuels mix, as shown in Section 4.3.1.4. Energy supply emissions peak at the same time in 2020 in both tier cases and across budget scenarios but follow slightly distinct trajectories post-2030 depending on the tier case. In the *2deg* scenario, CO_2 emissions from energy supply in the Tier 2 case are lower than in Tier 1. It is not immediately clear what causes this, but it is most likely a combination of several factors. Coal use is higher in the post-2030 period in Tier 2/*2deg* than in Tier1/*2deg*, but oil use is lower (Figure 4-10), so it is difficult to gauge what the balance might be from these sources without specifically delving into these variables. Likely, oil is replaced by bioliquids while coal electricity is replaced by bioelectricity. This suggests that lower emission factors in the agricultural phase of biomass production favors more biomass inclusion, as would be expected. On the other hand, energy supply mitigation is enhanced in the *1p5deg* scenario under Tier 2, affecting the mix of effort across the AFOLU and energy sectors.

These scenarios were not designed in a way to specifically examine these model choices, but, clearly, the choice of agricultural N_2O emission factors has ramifications that go well beyond the agricultural and land use sectors in these cost-optimal mitigation scenarios.

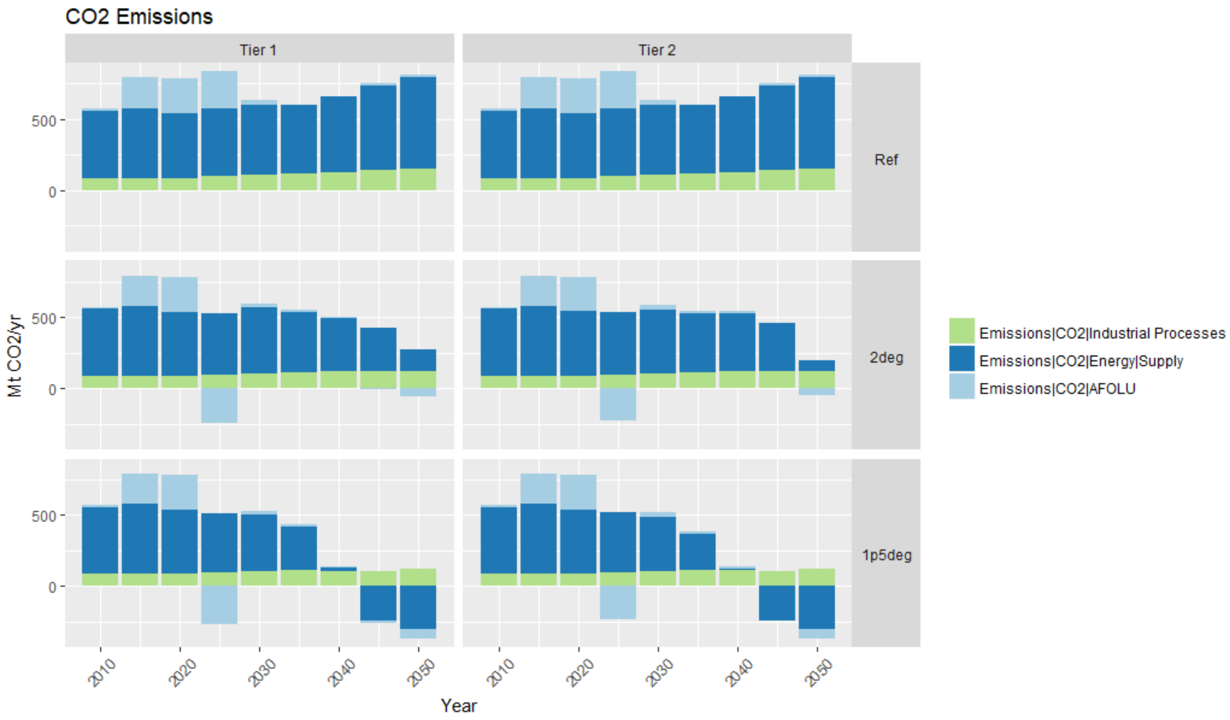

Figure 4-17 – CO_2 Emissions across scenarios and Tier cases

4.3.4.3 Methane

Methane emissions do not change appreciably with the implementation of the new N_2O emission factors.

4.3.5 Total GHG emissions profile

Figure 4-18 show Brazilian GHG emissions profile, comparing them across the Tier 1 and Tier 2 cases. As described in the preceding sections, the change in agricultural N_2O emission factors causes changes in the CO_2 and N_2O emissions in the modelled results. Moreover, it is expected that, eventually, the Brazilian GHG inventory will move to Tier 2 emission factors for non-CO_2 gases in the agricultural sectors, as is already done for CO_2 emissions in LULUCF (GofB, 2015a). Should future research confirm that Tier 2 N_2O emission factors for the case of Brazil are indeed lower than the IPPC Tier 1 default values currently used, this will cause an immediate drop in Brazilian reported GHG emissions, not only in the future, but also historic rates. This implies that Brazil in fact may have been overreporting GHG emissions, which could be good news for global efforts to curb climate change. This finding adds to the controversy around carbon budgets (MILLAR et al., 2017) and may affect results of global stock take exercises such as the UNEP Gap Report (UNEP, 2017).

However, as can be seen from Figure 4-18, the changes are not very large relative to the total emissions in Brazil. On the other hand, it is important to remember that BLUES does not (yet) capture all the N_2O emission sources through a Tier 2 approach. In particular, emissions from residues left on fields are still calculated through a Tier 1 method (Section 3.3.8.3). Future research should continuing to look into these effects as higher resolution data becomes available.

Figure 4-18 – GHG Emissions in Brazil across scenarios and cases

4.3.5.1 Carbon budgets and cumulative GHG emissions

Table 4-9 shows the difference in cumulative emissions of GHGs between Tier 1 and Tier 2 cases, showing variations in cumulative GHG emissions across scenarios in the BLUES solution.

Table 4-9 – Differences in cumulative emissions of GHGs between Tier 1 and Tier 2 cases

		CO_2	CH_4	N_2O	cum GHG
2 deg	**Mt of gas**	-5.02	16.65	-1.31	
	Gt of CO2eq	-0.005	0.52	-0.39	0.12
1p5deg	**Mt of gas**	-4.60	1.35	-1.54	
	Gt of CO2eq	-0.005	0.04	-0.46	-0.42

Positive values indicate an increase from Tier 1 to Tier 2

It is unclear what exactly is driving the changes in GHG emissions in the Tier 2 cases, since there are multiple routes through which this could be occurring. Since the CO_2 budget is fixed, changing the emission factors for N_2O should not affect cumulative CO_2 emissions, and this is indeed what happens[31]. This means the difference comes from non-CO_2 gases. Methane and nitrous oxide emissions are often associated with the same agricultural process as, for example, in livestock production. Therefore, changing the metric that defines the cost of one will automatically have impacts on the other. Unpacking these differences requires careful examination of results and possibly the need to run new diagnostic scenarios and is for this reason left for future research.

4.3.6 Conclusions

The results presented in this chapter indicate there are significant potential effects of the choice of agricultural N_2O emission factors on sectors other than agriculture and land use in scenarios exploring climate mitigation. Second order effects on the energy system solutions occur via bioenergy production and go beyond changing the mix of the crops used as feedstocks and their respective planted areas, affecting also the choice of biofuel production routes. On the other hand, power generation and vehicular fleet composition are robust to those changes, meaning they do not seem to change with the choice of emission factor.

These results raise an important question, namely, about whether modelling results from models implementing parameters based on Tier 1 emission factors are robust to that choice, or whether the solutions would change if other emission factors were implemented. Given the importance of tropical agriculture production to meet rising food demand, this is a question worth exploring.

It must be noted that the Tier 2 values were applied here as a single national average value for all crops taken from ALVES et al. (2010), who did a metanalysis of existing research on the topic. However, applying individual emission factor values from the literature to each crop might cause further changes in the solutions of the model, and should be analyzed as a further sensitivity in future research.

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[31] The minor change of 0.005 Gt CO_2eq represents a very small fraction of the total emissions budget, and is simply an adjustment well within the model’s solution uncertainty.

5. Conclusions and Final Remarks

This thesis described the development of a land use module was hard-linked to an existing energy system model to create the new BLUES model. It then explored interlinkages in the AFOLU and energy sectors (Case Study 1) and the role of non-CO_2 gases in the Brazilian emissions profile resulting from choice of agricultural N_2O emission factors (Case Study 2).

The BLUES model confronts mitigation options in the AFOLU and energy sectors directly by hard-linking the land use and energy sector modules to confront mitigation options in the AFOLU and energy sectors directly. Most IAMs have a soft-link approach between the energy and land use sectors, whereby solutions of the energy system and land use modules are serve as inputs for each other, usually transferred via spreadsheets or data tables of various formats. For example, the land use module may run first and send its solution back to the energy system module, adjusting its input for a new run whose solution is then sent back to the land use module which runs again. The process is repeated until a convergence of the two solutions is reached.

In the iteration between the land use and energy system modules, the latter provides to the former the demand level and the costs of bioenergy, while the former provide to the latter the available area for production and the productivity of the bioenergy feedstocks. The parameters exchanged between the different modules can also include emissions trajectories; international commodity (including bioenergy) prices and production or trade; and energy demand in various sectors or levels, but this varies with the model and may include more variables.

In many cases, there is also a macroeconomic module in the model, which interacts with the other two modules via a similar process. Some complex land use modules are actually made up of various sub-modules that include a crop model (giving yield potential of crops in various regions), a land cover model that reproduces native vegetation characteristics, land cover prices and/or infrastructure constraints. The level of complexity varies greatly across models, as well as the implementation method for each module. Including a macroeconomic module enables the inclusion of investment levels as an exchange parameter with the energy sector module, although this depends on the complexity of the former.

This soft-link approach means the modules find their individual solutions in isolation, albeit under the constraints set by the other modules. Still, this implies that mitigation options in different sectors are not compared directly, so that the energy sector module may choose a technological option that implies trade-offs in the other sectors. The impacts of this are minimized by ensuring that the ultimate decision variable (cost) is uniformly modeled across all modules. This, however, is not always easily done, and requires active collaboration between the teams of researchers running the various modules to ensure the basic assumptions are consistent across the different sectors in the integrated modelling framework. In many cases this consistency is limited to a few overarching assumptions such as GDP and population growth, and international commodity and emissions prices. Few teams can truly sync their models to ensure this self-consistency. This means there is the possibility that sub-optimal decisions reached in each sector are kept by the iterative process.

The advantages of hard-linking the energy and land use sectors boil down to the possibility to directly and simultaneously confront mitigation options in all sectors. This means the model chooses between, for example, deploying a low-carbon power generation technology or recovering a degraded pasture. It directly confronts the cost of a unit of mitigation for each and decides which to deploy depending on the constraints in place. This means the model dynamically assesses the costs and constraints, avoiding the pitfall of rigid costs and constraints that come from the passing of the solutions between each sub-module.

The main disadvantages of hard-linking sub-modules into one large consistent model are the sheer data requirement and computing power needed. Another disadvantage of hard-linking is that separate modules can tailor their architecture to the realities of each modelled sector. This however, may also raise issues of modelling consistency. For example, running a CGE or land use model in dynamic recursive mode but an energy systems model in perfect foresight mode means the modelled agents have different information in each case.

Aggregation and simplification help to address issues of data and computing power requirements. In the case of the BLUES model developed here, there is spatial aggregation of the land cover into non-gridded parameters. Therefore, the model is capable of telling the user how large the land use transitions need to be, but not where exactly they are taking place. This implies higher uncertainties in the carbon stock of the transitioned lands, and the resulting land use emissions.

Other sources of uncertainty in the land use results of BLUES have to do with the fact that the model was built using a platform that was originally conceived for the energy sector. One of the issues that arises has to do with the above-mentioned caveat of not being spatially explicit. In the real world, energy system emissions (and sequestration) occur immediately, that is, at the same time the process that generates (sequesters) the GHGs is used. This is how emissions are modelled in BLUES. Land use emissions, on the other hand, may be more diffuse across time periods. A case in point is the emission or sequestration of CO_2 by deforestation or by growing forests, respectively. For example, deforestation of tropical forests causes a pulse of emissions representing the majority of the biomass carbon in the original vegetation, which is usually burned for land clearing, followed by a more gradual emission from decomposition of the soil organic carbon. In contrast, the afforestation of abandoned areas to native vegetation occurs gradually over long periods until the full carbon stock of the original vegetation is restored. This is challenging to represent in a platform designed for energy systems modelling that deals with immediate emissions and sequestration. In BLUES, emissions and sequestration from AFOLU are modelled as pulses occurring at a single point in time. This may result in an overly-optimistic bias towards land-based sequestration through natural vegetation regrowth, especially in the short-term. In BLUES, this was countered by assuming conservative values for the sequestration parameters of afforestation processes.

As for the scenarios used in the case studies, a major source of uncertainty is the concept of carbon budgets. As noted in Section 4.1.1, the mitigation scenarios explored here[32] treat non-CO_2 gases differently than CO_2, in such a way that makes the budgets actually be CO_2 budgets, with non-CO_2 gases receiving a cost associated with their emissions. Because these emission costs are calculated on a CO_2-equivalent basis, and because N_2O has the highest emission factor of the three main GHG (the other two being CO_2 and CH_4), N_2O emissions become the most expensive in the way the model is set up. This implies the choice of N_2O emission factor will have a high impact on the costs of processes that emit this gas. Nitrous oxide is a gas mainly emitted in the agricultural sector, as explained in Section 2.3, a sector characterized by high uncertainties. In fact, the choice of agricultural N_2O emission factors often follow the Tier 1 default methodology of the IPCC for national inventory GHG calculations. That is indeed the case for Brazil. The literature, however, indicates that actual emission factors may be much lower than those calculated using Tier 1 methodology, some 50% lower (Section 3.3.8.3).

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[32] But this is also the modelling protocol often adopted by major IAMs.

Case Study 2 examined what the effects of the choice of agricultural N_2O emission factors (EF) are on the solution of the model, especially on the energy system. This analysis gave mixed results, with some variables in the energy system being affected, while others proved robust to the choice of EF. Specifically, the power generation sector proved robust to the choice of EF for agricultural N_2O, while the biofuels mix changed. The total production of biofuels remained the same since the composition of the vehicle fleet was also robust to the choice of EF, but the mix of biofuels changed considerably, especially in the preferred routes for production of advanced biokerosene and biodiesel.

Importantly, as was to be expected from a choice of lower EFs, the N_2O emissions decreased when using Tier 2 versus Tier 1. This points to the fact that the Brazilian official communications to the UNFCCC may be overreporting N_2O emissions, since it uses Tier 1 methodology due to the unavailability of empirical studies on national emission factors for N_2O. This highlights the need for additional research on non-CO_2 emission factors in Brazil, especially in the agricultural sector, in order to derive more accurate estimations of the emissions of these GHGs in Brazil. This has already begun, as evidenced by some of the studies referenced in this thesis, but further research is needed to determine crop-by-crop emission factors that also account for the management style employed in the cultivation process (conventional versus zero-till, for example).

The availability and reliability of existing data was and continues to be a challenge for the accurate representation of land use dynamics in Brazil. However, recent advances have shown this is a fast-moving field, and certainly advances are already available which need to be incorporated into the model. Updating and validating BLUES should be an ongoing effort, with reviews occurring regularly, with a recommendation for at least an annual update in the first few years.

Future research applying the BLUES model includes the implementation of crop-specific EFs to test the impact on GHG emission mitigation scenarios. The present analysis implemented an average value derived from a study by EMBRAPA. Another future topic, a sensitivity analysis on the EF choice for sugarcane, elephant-grass, eucalyptus and soybeans may yield interesting insights into the mitigation potential of each as a feedstock for bioenergy production. In addition, technical GHG emission abatement options exist for agricultural processes which have not yet been implemented in BLUES. This should be part of upcoming model development efforts.

Summarizing the thesis, first a literature review of the relevant topics was conducted (Chapter 2) to lay the theoretical and conceptual basis for the following chapters. Next, the methodology and data utilized in the creation of BLUES was explained in Chapter 3. Chapter 4 presented two case studies applying the newly created model, including a description of the scenarios used in the case studies. These case studies are examples of the type of analysis made possible by the BLUES model. Case Study 1 explored the linkages between the energy sector and AFOLU sectors, while Case Study 2 explored the impacts of the choice of agricultural N_2O emission factors on the solution of the BLUES model.

As explained in Section 4.1.4, there are differences between the two versions of BLUES used to generate the scenarios in each case study. These include the explicit modelling of nitrogen and carbonate application rates and the regionalization of methane emission factors by livestock. Case Study 1 had a top-down methodology implemented for agricultural emission factors for N_2O, while Case Study 2 used an updated version of the model with improved agriculture modelling.

The improvements to the version used in Case Study 2 include explicit representation of nitrogen fertilizer application in croplands and methane emission factors from livestock that were both regionalized and varied according to land cost classes. These changes represent step improvements in model development driven by shortcomings identified at each step. It is therefore to be expected that the emissions resulting from each version will differ. Table 5-1 shows the resulting cumulative GHG emissions for the period 2010-2050. The large differences between case Study 1 and Case Study 2 are a combination of differences in methane and nitrous oxide emissions. Methane emissions go up considerably with the regionalization of the emission factors, which is partially compensated for by the reduction in emissions of nitrous oxide due to the lower emission factors. What the table indicates is that the more detailed representation of the agricultural inputs are more significant than the single improvement measure of changing the emission factors for agricultural N_2O from Tier 1 to Tier 2.

Table 5-1 – Differences in cumulative emissions of GHGs between Tier 1 and Tier 2 cases. (in Gt CO_2eq/yr)

	Case Study 1	Case Study 2/Tier 1	Case Study 2/Tier 2
Ref	67.0	88.8	86.5
2 deg	50.3	73.0	71.7
1p5deg	41.7	65.1	63.6

Ref	--	+33%	-3%
2 deg	--	+45%	-2%
1p5deg	--	+56%	-2%

Percentages in the bottom rows indicate the variation from progressively more detailed implementation (left to right).

The main conclusions of the thesis include:

- Hard-linking of various sectoral sub-modules allows simultaneously solving multi-sectoral problems, avoiding sub-optimal decisions carried through by the iterative process inherent to soft-link approaches.
- There are strong interlinkages between AFOLU and energy sectors mainly via biofuels, with the transportation sector being most sensitive to constraints in AFOLU.
- Changes in the transportation sector also affect deployment of bioenergy, especially the electrification of the LDV fleet, which causes a change in demand for biofuels.
- Choice of emission factors are important and the Tier 1 emission factors so far used in Brazilian AFOLU are likely to have been too high, meaning an overreporting of non-CO_2 gases is likely to have occurred in past inventories.
- Second order effects of the choice of agricultural N_2O emission factors are significant in the energy sector for cost-optimal mitigation scenarios.
- Future research should expand the analysis to include Tier 2 EFs for all crops and for some of the processes that are part of livestock production activities.
- These second order effects highlight the importance of choosing appropriate emission factors that are specifically estimated for Brazil, a call to action for further empirical research on the subject.

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Appendix 1

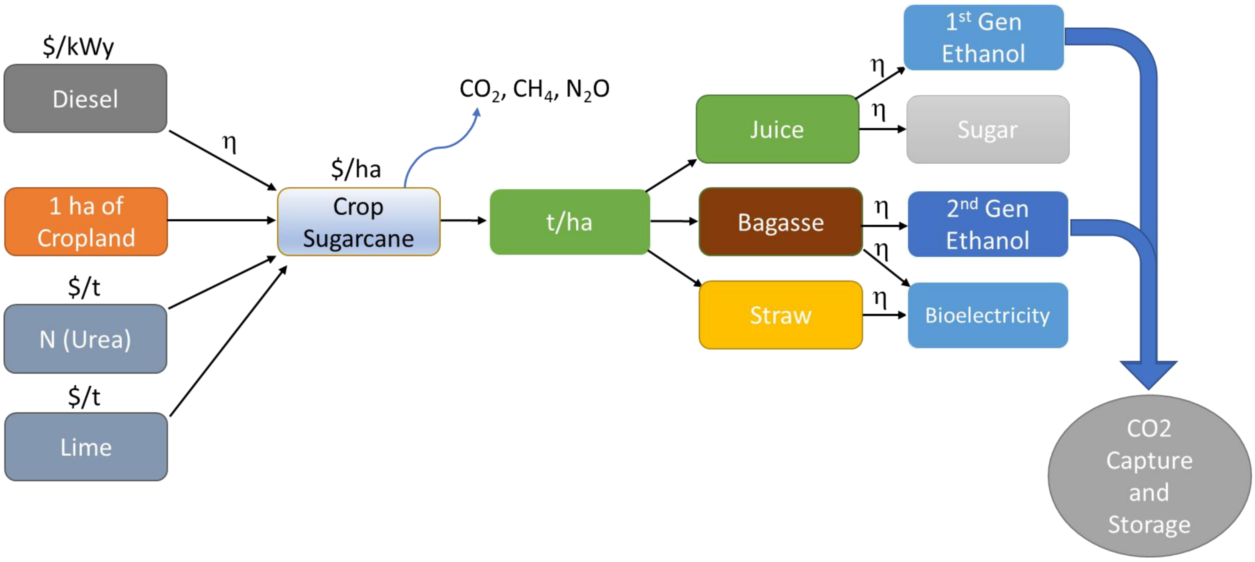

Figure A1 – The sugarcane chain in COPPE-MSB and in BLUES