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ORIGINAL RESEARCH

The impact of land-use change emissions on the potential of bioenergy as climate change mitigation option for a Brazilian low-carbon energy system

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Abstract

Land-use change (LUC)-related greenhouse gas (GHG) emissions determine largely whether bioenergy is a suitable option for climate change mitigation. This study assesses how LUC emissions influence demand for bioenergy to mitigate GHG emissions, and how this affects the energy mix, using Brazil as a case study. A methodological framework is applied linking bioenergy supply curves, with associated costs and spatially explicit LUC emissions, to a bottom-up energy system model. Furthermore, the influence of four key determining parameters is assessed: agricultural productivity, time horizon, natural succession (NS), and the use of dynamic emission factors (EFs). Demand for new bioenergy plantations range from 0.5 to 6.7 EJ in 2050, and is avoided when its EF reaches above 15 kg $CO_2/GJ_{biomass}$. Dynamic EFs result in earlier and larger use of bioenergy. Static EFs attenuate all emissions evenly over time, resulting in relative high emissions around 2050 when the carbon budget is most stringent. This in contrast to dynamic EFs, having early high peaks because of clearance of natural vegetation, but relatively small long-term emissions when the carbon budget is most stringent. Exclusion of NS, in combination with spared agricultural land, results in a demand of 6.7 EJ, because of its low carbon penalty. Assuming that land is spared due to continuous yield increase (which is the reason to include NS as and EF component), bypasses the fact that yield improvements (that make those lands available) take place because of demand for bioenergy. When low-carbon biomass is in limited availability, increasing electrification is observed, leading to electric capacity increase of 62% (mainly wind and solar energy), and a 12% energy system costs increase. Inclusion of spatiotemporal explicit supply potential and LUC emissions leads to improved bioenergy deployment pathways that come closer to the real situation as the dynamic nature of LUC emissions is included.

KEYWORDS

bioenergy, Brazil, climate change mitigation, energy system modelling, energy transition, greenhouse gas accounting, land use change, natural succession, reference system, sugarcane

1 | INTRODUCTION

To prevent mean global temperatures from surpassing 2°C above pre-industrial levels, biomass is regarded as an important climate change mitigation option (IPCC, 2018). The potential role of bioenergy in a low-carbon energy system depends mainly on the costs and the greenhouse gas (GHG) emission reduction potential of bioenergy in comparison to other low-carbon energy sources (Creutzig et al., 2015). The majority of these emissions are related to land-use change (LUC) induced by the cultivation of energy crops. In general, the effectiveness of the use of biomass as climate mitigation option is assessed by comparing the associated GHG emission factor (EF) per unit of energy, with the avoided fossil counterpart (Plevin et al., 2015). However, key parameters affecting the EF for bioenergy such as, for example, agricultural yields and (soil) carbon stocks are spatially heterogeneous (Albanito et al., 2016; Doelman et al., 2018), while methodological choices such as the selection of the time horizon (TH) (Plevin et al., 2015) and accounting for natural succession (NS) (Kalt et al., 2019) heavily influences bioenergy EFs. Therefore, a spatially temporal explicit method is required to quantify the EFs of bioenergy, and additionally its spatial-explicit costs.

The demand for bioenergy is driven by the associated EFs due to decarbonization policies. In principle, there will be higher or lower demand for bioenergy, dependent on its EF. When analyzing low-carbon energy system trajectories, the dynamic interaction between low-carbon supply and demand for bioenergy is required to obtain more precise modeling results (Gambhir et al., 2019), together with an improved model representation of the interaction between land and energy systems (Creutzig et al., 2015). This dynamic interaction is typically well studied with the so-called integrated assessment models (IAMs). However, their global scale usually comes with low spatial resolution (Wicke et al., 2015; Woltjer et al., 2017), and individual countries are modeled in a simplified way (Fragkos et al., 2018). It also contradicts with the strategy proposed in the Paris Agreement, calling for national climate mitigation strategies (UNFCCC, 2015). As climate policy and techno-economic performance of technologies, capital dynamics and constraints, and energy demand vary widely per country, national models can be preferred above global models to assess the transition toward low-carbon energy systems (Fragkos et al., 2018; Krey et al., 2018).

Limited studies have investigated the dynamic link between spatially explicit GHG quantification of bioenergy and national energy systems, which is recommended by Köberle (2018) for assessing GHG mitigation strategies. Czyrnek-Delêtre et al. (2016) claim to be the first to assess the impact of LUC emissions on the demand for bioenergy in a low-carbon energy system. They show that the total primary bioenergy demand reduces with approximately 70% when LUC emissions are included, compared to a scenario excluding LUC emissions, resulting in radical changes especially in a low-carbon transport sector. However, they only use bioenergy EFs that are static over time, and constant over space.

Daioglou et al. (2017) and more recently Kalt et al. (2020) developed a spatiotemporal method to quantify the EFs related to bioenergy production (BP). They show the global supply potential of bioenergy per unit of associated GHG emissions, resulting in the so-called emission supply curves, as originally proposed by Haberl (2013). However, both studies do not assess the dynamic interaction for multiple end-use application for biomass (e.g., electricity production, renewable heat for the industry, feedstock for bio-chemical production), as they only assess the impact for biomass and BP. Furthermore, they did not investigate how these EFs affect bioenergy deployment strategies when trying to meet strict GHG constraints. Linking an energy system model to the emission supply curves, as developed by Daioglou et al. (2017), allows for the assessment of impact of LUC emission on biomass as climate change mitigation option because (1) it includes the spatial heterogeneity of LUC, (2) the dynamic interaction between supply and demand for bioenergy can be assessed, and (3) the competition between various end-uses for bioenergy can be assessed.

The aim of this study is to assess how LUC-related GHG emissions (hereafter LUC emissions) influence the demand for bioenergy as an option for climate change mitigation, and how this affects domestic final energy mix, within the time frame 2010–2050. A framework of a linear optimization energy system model, combined with a stylized representation of marginal LUC emissions from biomass production, is used to analyze this. Brazil is chosen as case study because the country has globally one of the largest biomass potentials (IRENA, 2014; Welfle, 2017) and is currently the second biggest biofuel producer (IEA, 2019). Furthermore, studies that analyze low-carbon energy pathways show that bioenergy is expected to be the prime source of energy for the Brazilian energy system by 2050 (Lap et al., 2019; P. Rochedo, 2016). However, historically the majority of the Brazilian GHG emissions is related to land use (Ministerio de Estado da Ciencia, Technologia, Inovacoes e Comunicacoes, 2017). This raises the question whether or not Brazil can produce bioenergy while also contributing to net GHG emission reduction strategies. Furthermore, this methodological framework is used to evaluate key parameters that influence the supply potential and/or the EF of bioenergy as climate mitigation option: agricultural productivity, selection of TH, accounting for NS, and the use of temporal dynamic EFs.

2 | INTRODUCING KEY DETERMINING PARAMETERS

Quantification of bioenergy supply potential and related LUC emissions depends on multiple parameters. The influence on the demand for bioenergy as an option for climate change mitigation of four key determining factors is assessed in this study. These factors are introduced below, also in relation to how bioenergy is modeled in energy system models.

2.1 | Agricultural productivity

Agricultural productivity shows how much agricultural products can be produced per unit of land. Over the past 60 years, global trends show increasing productivity for the major agricultural products (FAOSTAT, 2020; Gerssen-Gondelach et al., 2015). Forecasts toward 2050 show increasing productivity (Alexandratos & Bruinsma, 2012), mainly because there is still a yield gap, which can be overcome by, for example, improvements in agricultural management and better use of fertilizer (Lobell et al., 2009).

Increasing agricultural productivity can result in abandonment of agricultural land, which can become available for BP. The carbon debt on abandoned agricultural lands is relatively low because of limited vegetation (Fargione et al., 2008). Agricultural productivity influences the supply potential for bioenergy on abandoned agricultural lands with a relative low carbon footprint.

2.2 | Time horizon

The selection of a TH over which LUC emissions are amortized influences the EF of bioenergy (Plevin et al., 2010). In general, the majority of the LUC emissions occur during the conversion from one land type to another, due to clearings of the living biomass (Wise et al., 2015). When this spike in emissions is amortized over a longer TH, the EF per unit of produced energy is lower. The effect of choosing a specific TH will have large influence on the bioenergy EF as carbon stocks change over time (Koponen et al., 2018).

2.3 | Natural succession

When agricultural lands become abandoned in the future, the natural vegetation (NV) can grow back. Regrowth of NV is called NS. Accounting for NS on abandoned agricultural land (Kalt et al., 2019) affects bioenergy EFs. While the accounting for NS is usually not included in bioenergy GHG assessments (Searchinger et al., 2017), a growing number of studies highlight the importance of accounting for NS as an EF component. By including NS as an EF component in bioenergy GHG accounting methods, it is assumed that land is spared, because of yield increase (Albanito et al., 2016).

However, the reason this land can be spared is not directly due to yield increases as such, but because of climate mitigation policy: there is a demand for low-carbon energy carriers. This demand can create incentives to spare agricultural land since this has a high potential for low-carbon bioenergy and does not result in indirect LUC (Wicke et al., 2012). Therefore, NS does (in many settings) not happen automatically, but because the land is spared with a very specific goal: provide low-carbon bioenergy to fulfill energy demand. Without this demand, it is less likely that land is spared and NS will occur.

Furthermore, the impact of NS on carbon stocks is steadily decreasing over time since it will reach an equilibrium. The annual carbon savings therefore decrease over time, while the carbon savings from BP remain and accumulate. From a farmers' perspective, a stable long-term economic prospective is important in the decision to switch to another type of farming. The fact that the NS EF component should be included in bioenergy GHG accounting methods, does therefore not necessarily stand ground and is transparently investigated here.

2.4 | Dynamic emissions

In energy system models, the emissions from energy carriers are based on the consumption of energy carriers (e.g., coal, diesel, and natural gas). The fixed carbon content of these carriers causes fixed emissions when combusted. To calculate the GHG emissions, a fixed EF is linked to the consumption of an energy carrier. For bioenergy, this is different. First of all, the carbon content of the bioenergy is short cyclic. The source of the carbon is atmospheric CO_2 embodied in the biomass by photosynthesis. When the bioenergy is combusted, that same CO_2 is emitted into the atmosphere again; in other words, the bioenergy is CO_2 neutral. In simplified models, this is also how bioenergy emissions are defined. However, this does not account for LUC emissions. LUC emissions happen during different stages of the production of bioenergy. Emissions from clearing NV for new bioenergy plantations happen instantly, while emissions from decreasing soil organic carbon occur over a longer period, just like emissions related to bioenergy cultivation. The temporal dimension of LUC emissions is dynamic, in contradiction to the static emissions of conventional hydrocarbon fuels.

Lifecycle assessments present LUC EFs normally as one single EF. This can be done when choices are made with respect to system boundaries (e.g., TH, allocation assumptions, carbon stock changes). This single bioenergy EF can be used in energy system models just like conventional hydrocarbon fuels (as done in Czyrnek-Delêtre et al., 2016). However, by including those (static) EFs, the temporal dynamic nature of short- and long term LUC emissions is not captured.

2.5 | Influence of key determining factors on modeling bioenergy

Bioenergy is included in energy system models on the supply side of the model per type of feedstock with the associated roadside costs, its EF, restricted by its supply potential. In Table 1, an overview is given how the key determining factors influence the way bioenergy is modeled in ESMs, and how it affects the results of low-carbon energy system assessments.

3 | MATERIALS AND METHODS

To assess the impact of LUC emissions on the demand for bioenergy in a Brazilian low-carbon energy system, two main approaches are combined, as illustrated in the framework of this assessment (Figure 1). First, the spatially explicit supply potential of biomass with the associated GHG emissions is calculated: the biomass GHG supply curves (see Section 3.4 for details). These show how much biomass can be supplied given the associated GHG emissions and costs for each potentially available location in Brazil, on lands with NV and on abandoned agricultural land. Agricultural lands are excluded as a location as a “food first” principle is applied to avoid competition with food production and indirect LUC.

Scenario analysis is used to assess the key determining parameters of the bioenergy supply potential and EFs. The developed bioenergy GHG supply curves are linked to the least-cost optimization model TIMBRA (The Integrated Market allocation Energy flow optimization System—BRAzil), showing the lowest cost solution to meet the demand for energy under a strict carbon budget. Within TIMBRA, an extensive portfolio of (low-carbon) energy carriers and conversion technologies is assessed based on costs and GHG emissions. The economic competition between different low-carbon energy sources is assessed, given a specific carbon budget. Therefore, this framework allows to analyze how much biomass will be used given its GHG emissions and costs, in relation to other low-carbon technologies, and when biomass (and other energy carriers) is used within the timeframe 2010–2050.

3.1 | TIMBRA

The Integrated Market allocation Energy flow optimization System—BRAzil is a linear optimization energy

TABLE 1 Overview of key determining factors, and how they affect the modeling of bioenergy in energy system models

Key determining factor	Bioenergy parameter ESM affected	Description: effect on modeling results
Agricultural productivity	Supply potential and EF	Agricultural productivity determines how much land is available for each biome type and what is the productivity of the bioenergy crop, leading to the supply potential of bioenergy Furthermore, it determines abandonment of agricultural land. Due to the low carbon debt of those lands, agricultural productivity influences this low-carbon supply potential. In ESMs with GHG targets, this low-carbon supply potential is favored above bioenergy with high EFs
Time horizon	EF	The higher the time horizon, the lower the total EF of the bioenergy. In GHG-restricted energy system assessments, this plays an important role whether or not biomass is selected as a cost-effective low-carbon energy option, above other options
Natural succession	EF	When included, the EFs of bioenergy from abandoned agricultural lands increase, and the bioenergy become less attractive as a low-carbon source in ESMs with GHG targets The effect of natural succession only appears when agricultural land is abandoned, driven by agricultural productivity
Dynamic emissions	EF	Modeling bioenergy with dynamic EFs does influence the temporal deployment prospective of bioenergy. Higher short-term EFs (which are attenuated, because spread out over time when static EFs are used) can weaken the demand when carbon restrictions become stringent, resulting in shifting strategies (other low-carbon technologies, and/or different timing of bioenergy deployment) to meet both energy demand and GHG emission restrictions

Abbreviations: EF, emission factor; GHG, greenhouse gas.

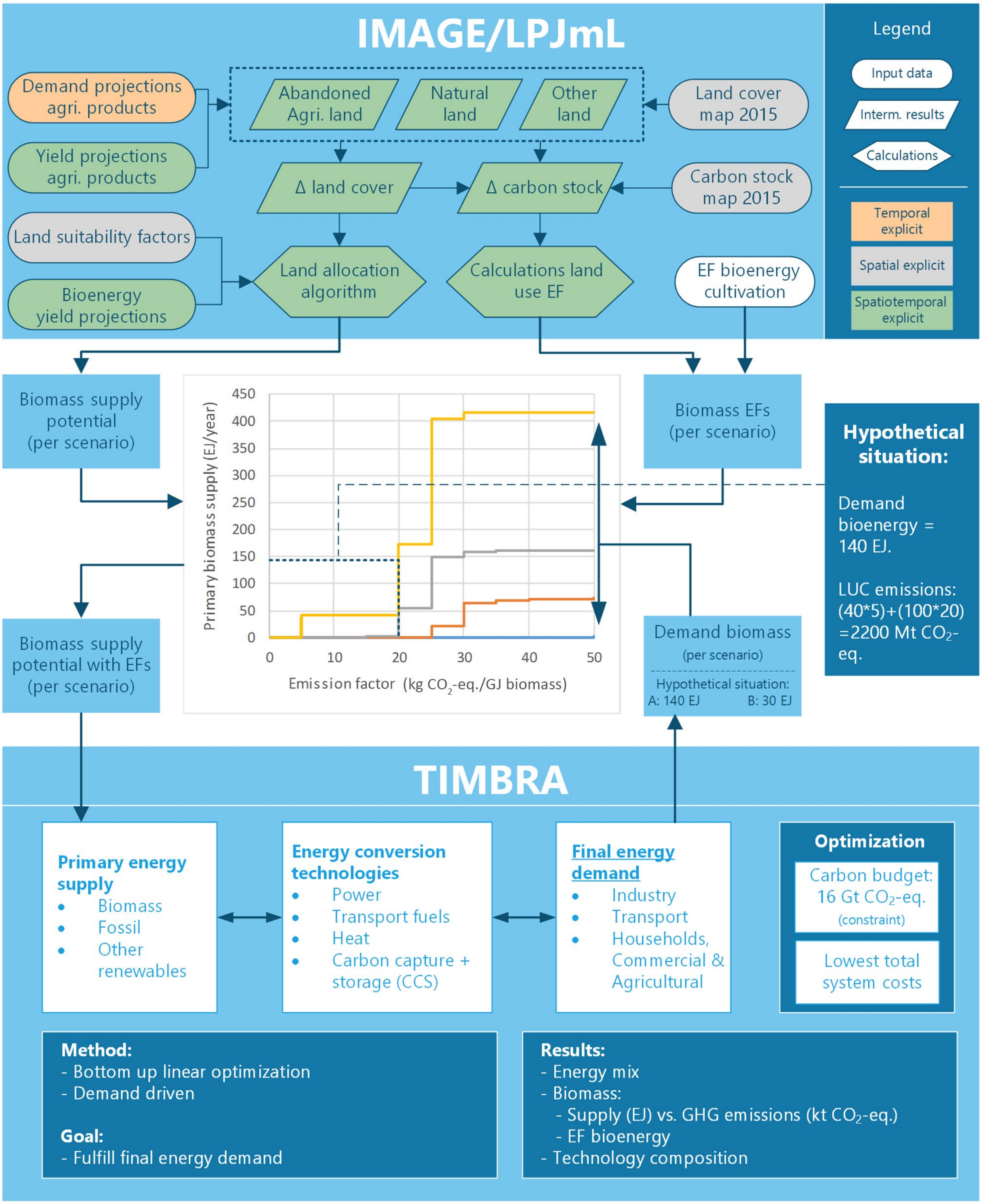

FIGURE 1 Overview of the methodological framework. Including the methodological approach for the GHG supply curves (on top), the methodological framework of TIMBRA (bottom), and how they are linked (middle). The timeframe of the study is from 2010 to 2050, with time slices each 5 years. TIMBRA makes a consideration between the supply of biomass (to fulfill energy demand), and the accompanying LUC emissions that needs to fit into the carbon budget. In the hypothetical situation there is a demand of 140 EJ for bioenergy, which comes with a total of 2.2 Gt CO_2-eq. (40 EJ with an EF of 5 kg CO_2-eq./GJ, and 100 EJ with an EF of 20 kg CO_2-eq./GJ). GHG, greenhouse gas; LUC, land-use change; TIMBRA, The Integrated Market allocation Energy flow optimization System—BRAzil

system model which is used to minimize energy system costs for Brazil under a set of user-defined restrictions for the period 2010–2050 (Nogueira, 2016). TIMBRA is used to assess the dynamic interaction between primary energy carriers, a list of conversion technologies and end-use demand in the main sectors (industry, transportation, residential & commercial, agriculture, and non-energy).

The three types of biomass supply potentials are input data for TIMBRA: current energy crops, residues, and new bioenergy plantations (see Section 3.2 for details). Bioenergy can be used in the following end-use sectors: industry, transportation, residential & commercial, and non-energy. The possible pathways for biomass to fulfill energy demand from the bioenergy crops, via conversion technologies, to end-use applications is depicted in Figure A1-1 (Appendix S1). The technology portfolio also includes (bioenergy) carbon capture technologies. The supply potential other than biomass is obtained from scientific literature for fossil (Saraiva et al., 2014), nuclear (Deutch et al., 2009), hydropower (Empresa de Pesquisa Energética, & Ministério de Minas e Energia, 2007), wind (Lap et al., 2020), and solar (Malagueta et al., 2014; Miranda et al., 2015) resources.

The techno-economic characteristics of the conversion technologies (bio-based, fossil, and renewables) are found in Lap et al. (2019). The cost assessment in TIMBRA is based on capital costs (CAPEX) and operational costs (OPEX) of energy conversion technologies, and on fuel costs (Loulou et al., 2005) and changes over time. The annual supply cost of the entire energy system cover the same cost categories and exclude costs on the demand side that convert final energy to useful energy. The demand for energy is an exogenous input for TIMBRA, and is obtained from demand projections for Brazil based on future estimates on demographics and GDP statistics (Nogueira, 2016; P. Rochedo, 2016).

3.1.1 | GHG emission budget

Climate policy is included in TIMBRA by applying a carbon budget. The carbon budget is the volume of GHG emissions that Brazil may emit (for the period: 2010–2050) to prevent global warming from surpassing the two degree Celsius limit, and is set to 16 Gt CO_2-eq. in this study according to estimates from Rochedo et al. (2018). In this study, the carbon budget is associated only to the energy system (see Figure 2). The emissions from LUC for BP, and the emissions related to the cultivation of those bioenergy crops are thus included in the carbon budget for the energy system. The accumulated GHG emissions of new bioenergy plantations can be compared with the carbon budget to analyze the allowable GHG emissions of those plantations.

Although the LUC emissions from the bioenergy plantations are in principle regarded as emissions related to the Agriculture, Forestry and Other Land Use (AFOLU) sector, they are in this study explicitly assigned to the energy sector. This is because bioenergy is regarded as a decarbonization option for the energy sector. Since the aim of this study is to investigate the potential of bioenergy as a decarbonization option, the LUC emissions are explicitly assigned to the energy sector.

Additional land-use-related GHG emissions (i.e., from deforestation, enteric fermentation, nitrogen fertilization) that are not directly associated with energy production are therefore excluded from the carbon budget for the energy system as used in this study. This distinction is made because the primary drivers for GHGs from the agricultural sector are related to agricultural demand in general (Câmara et al., 2015), and more specifically to beef production (Cohn et al., 2014) and soybean cultivation (Nepstad et al., 2014). By decoupling the carbon budget,

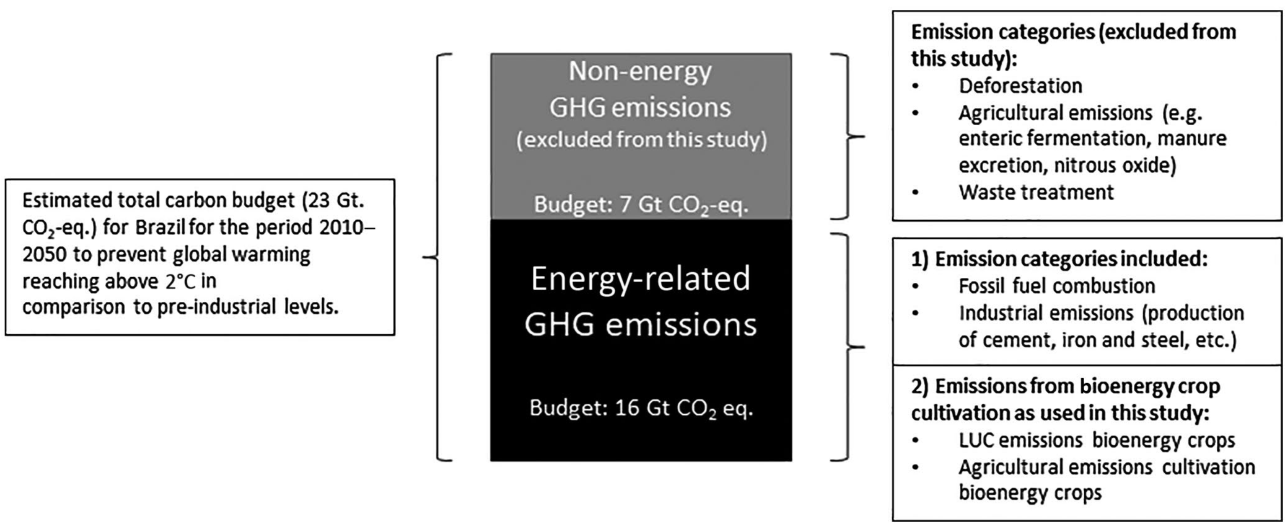

FIGURE 2 Carbon budget as used in this study for Brazil during the period 2010–2050. GHG, greenhouse gas; LUC, land-use change

specific emphasis is put on energy-related LUC emissions within a defined energy-related carbon budget.

GHG emissions of the energy sector are included in TIMBRA by multiplying primary energy consumption with the associated EFs (Lap et al., 2019). This includes also upstream GHG emissions for both fossil and renewable energy.

3.2 | Bioenergy supply potential and EFs

In this study, three different types of bioenergy supply potential are distinguished. Supply potential from:

1. New bioenergy plantations
2. Current bioenergy crops
3. Agricultural residues

The supply potential of new bioenergy plantations is described in Section 3.4. The supply potential of current bioenergy crops consists of the supply potential from land cultivated with energy crops in 2015. It is assumed that the area of energy crops under cultivation in 2015 already affected the carbon stocks. This supply potential relates to sugarcane, oil from soybeans (excluding the use of soybean oil for human consumption and other non-energy use in Brazil, based on food supply and for other use than food or energy, FAOSTAT, 2020; MME, 2016), and wood plantations for industry. This supply potential can increase over time due to yield improvements (dependent on the scenario), given the fixed acreage in 2015. As the demand for sugar is assumed to be a non-energy commodity, growth in demand for land that is required to meet the demand for sugar is assumed to be used for food production. No EF is associated with the growth of sugarcane production area due to demand increase for sugar production, although the co-products are used for energy purposes.

The supply potential of agricultural residues consists of rice husk, soybean straw, maize stover, and sugarcane straw in this study. These crops are selected because they represent the majority of the total crop production in Brazil (FAOSTAT, 2020), and have a high crop-to-residue potential (Portugal-Pereira et al., 2015), subsequently showing the highest potential for energy production from agricultural residues. The supply potential in this study relates to the *sustainable available potential*, assuming part of the residues is used as feed (Portugal-Pereira et al., 2015), and approximately 70% is left on the field to sustain ecological functioning of the soil, including a stable soil carbon stock (Carvalho et al., 2017; Daioglou et al., 2016).

For rice husk, soybean straw, and maize stover, an EF is added for carbon losses due to removal of residues, based on Mouratiadou et al. (2020). No EF is added for sugarcane straw. Recent studies show that the soil carbon stocks remain stable when 30% of the sugarcane straw is removed (Carvalho et al., 2017; Cherubin et al., 2018). The EF used for soybean oil is obtained from Hoefnagels et al. (2010). The supply potential of the mentioned residues is directly linked to the demand for food (see Section 3.4). For existing energy plantations, an EF is added for NS, based on carbon sequestration rates for regrowth of NV as described in Appendix S5.

3.3 | Cost–supply curves

The costs of biomass are incorporated in this study as cost–supply curves, where the supply potential of biomass crops is given in relation to the associated costs. The bioenergy cost–supply curves are obtained from Daioglou et al. (2016) for residues and Daioglou et al. (2019) for energy crops. Considered cost factors are cultivation, harvest, collection, storage, drying, and transport costs. Detailed information on the methods of the cost-supply curves can be found in Daioglou et al. (2016).

3.4 | GHG supply curves of new bioenergy plantations

The bioenergy GHG supply curves show the potential supply of new bioenergy plantations, with the associated GHG emissions (soil organic carbon, living biomass, and crop cultivation). The quantification of both supply potential and LUC emissions on a spatiotemporal level allows to assess the GHG mitigation potential of biomass in comparison to other energy carriers.

The bioenergy GHG supply curves are calculated using the dynamic interlinked IMAGE-LPJmL model. The latter model calculates the yield of crops by incorporating all biotic and abiotic factors. More details of the LPJmL model are found in Müller et al. (2016). Details about the integration of LPJmL in IMAGE to derive GHG supply curves are found in Daioglou et al. (2017). Per grid cell (30 × 30 arcminutes, circa 50 km at the equator), the potential supply of a type of biomass is calculated using the dynamic vegetation model LPJmL. The yield calculated by the LPJmL model is the attainable yield (benchmark for rain-fed crops; Fischer et al., 2012). The considered crop is sugarcane, as this crop shows the highest energy potential (Gerssen-Gondelach et al., 2014), and is currently among the most cultivated crops in Brazil (FAOSTAT, 2020). Miscanthus or eucalyptus can potentially be important energy crops. Due to differences in biophysical properties, growing locations (with different soil carbon stocks) can change, potentially resulting in better EFs. The difference between those three crops is discussed in Appendix S4. The biomass from clearing NV for new bioenergy plantations is not used as bioenergy feedstock in this study, mainly because of concerns with quality (Daioglou et al., 2017).

For each grid cell assigned to Brazil, the biomass production and associated EF are calculated within the IMAGE model. Finally, by ordering the grid cells according to their EF, and cumulating their potentials, the GHG supply curve is created. As the supply potential for entire Brazil is calculated, a distinction is made in the results between full supply potential and low-carbon supply potential. Low-carbon supply potential is defined in this study as the supply potential with an EF below 15 kg $CO_2/GJ_{\text{primary biomass}}$. This value is in line with standards set in the renewable energy directive (RED) of the EU (European Parliament, 2018), which defines that bioenergy should have a 70% reduction in terms of GHG emissions compared to its fossil counterpart. The GHG supply curves are obtained from analyses of Daioglou et al. (2017) and are adjusted (see Appendix S2) to be used as input data for the TIMBRA model.

Land is classified into agricultural lands and NV for all time steps. The NV is further differentiated by the LPJmL model into biome types: tropical forests, temperate forests, and savannah. In this study, it is assumed that the potential production of bioenergy will take place on land with NV or on abandoned agricultural land. Abandoned agricultural land is land that becomes available when land demand for crops or livestock systems decreases due to either reallocation of crops to more suitable locations or yield increases, which is calculated within the LPJmL model. Urban areas and water areas are excluded from this study for energy crop production.

The yield developments and demand for agricultural products are based on the shared socio-economic pathway (SSP) scenarios as used in Doelman et al. (2018). The area of agricultural land that becomes abandoned, or expands over time is obtained from Daioglou et al. (2019) which uses the same input data from Doelman et al. (2018). When the agricultural area expands (at the expense of natural land), this area is still classified as agricultural land that is not available for BP (food-first principle). The majority of the spared land in the future is a result of intensification of low-intensity pastures (Doelman et al., 2018).

3.4.1 | EFs for GHG supply curves

The GHG emissions accounted for are (1) the emissions related to changes in soil carbon stocks and living biomass and (2) the associated emissions for the cultivation of the energy crops: fuel use for machinery and nitrogen application (see Daioglou et al., 2017 for more information). All EF components are described in Table 2.

TABLE 2 Emission factor (EF) components for the GHG emission supply curves

GHG EF components	Equation part	Description GHG EF component
Soil carbon stock changes	$(\text{C stock}_{nv} - \text{C stock}_{bp})$	The difference between changes in carbon (C) stocks (included are litter and soil organic carbon) for the NV and BP case. Calculated for each grid cell
Embodied carbon	$\text{C stock}_{\text{living bm}}$	Losses due to LUC as a result of removing carbon embodied in living biomass (above and below ground) from the existing NV
Emissions cultivation energy crops	$\text{BP}_{\text{cultivation}}$	• Fuel consumption machinery use • Nitrous oxide emissions from fertilizer application
Forgone emissions from natural succession	C stock AAL_{nv}	Abandoned agricultural land (AAL) is assumed to return to the NV: natural succession. Over time carbon stocks (soil and living biomass) will increase on these lands

Abbreviations: BP, bioenergy production; GHG, greenhouse gas; LUC, land-use change; NV, natural vegetation.

For spatiotemporal quantification of LUC emissions, the dynamics over time and space should be incorporated. Therefore, two different cases are modeled within IMAGE-LPJmL: a NV case where no bioenergy is produced, and a BP case. The difference in carbon stock change between both cases gives the GHG emissions related to carbon stocks. The EF per unit of energy produced is calculated for each grid cell g using Equation (1) (after Daioglou et al., 2017). The EF components are described in Table 2.

$$\text{EF}_g = \frac{(\text{C stock}_{nv} - \text{C stock}_{bp}) + \text{C stock}_{\text{living bm}} + \text{C stock AAL}_{nv}}{\sum_{2015}^{t_{\text{horizone}}} \text{Biomass potential}_g} + \text{BP}_{\text{cultivation}}. \tag{1}$$

To assess the effect of the dynamic LUC emissions, the static EFs from Daioglou et al. (2017) are split into short-term EFs (from clearing NV), and long-term EFs (for gradual changes over the entire TH), using the fraction between short- and long-term EFs (Equation 2). The short-term EF is allocated to the first TIMBRA time slice (of 5 years), while the long-term EF lasts for the entire TH.

$$\mathrm{EF(dynamic)}_{c,b,y,s} = \mathrm{SP}_{c,b,y,g,s} \times \mathrm{EF(static)}_{c,b,s} \times \mathrm{EFfraction}_{c,b,s}, \tag{2}$$

EF (short-term) = the short-term EF (kg CO_2-eq./$GJ_{(\text{prim. biomass})}$) of the selected bioenergy crop *c*, of biome *b*, at year *y* for the selected yield scenario *s*. SP = supply potential (GJ) of the selected bioenergy crop *c*, of biome *b*, for grid cell g, at year *y* for the selected yield scenario *s*. EF (static) = the static EF (kg CO_2-eq./$GJ_{(\text{prim. biomass})}$) of the selected bioenergy crop *c*, of biome *b*, for the selected yield scenario *s*. EF fraction = the fraction (%) of the short- or long-term EF from the static EF of the selected bioenergy crop *c*, of biome *b*, for the selected yield scenario *s*.

3.4.2 | Temporal dimension of the GHG supply curves

The development of demand for agricultural land over time depends (among others) on demand for agricultural products (food, feed, forestry products, and livestock) and yields. The agricultural land area (including the area that becomes abandoned over time), yields and demand for agricultural products are obtained from Doelman et al. (2018), and are based on the SSP scenarios. The majority of the spared land in the future is a result of intensification of low-intensity pastures (Doelman et al., 2018). The second reason is due to yield development over time of the selected bioenergy crop. In this analysis, it is assumed that bioenergy can be produced on abandoned agricultural lands and other natural lands (excluding forests and water stressed areas), in line with Daioglou et al. (2019).

The bioenergy GHG supply curves are time dependent because it is assumed the yield, and land availability of the bioenergy crops develops over time. The relation between supply potential, yield and land availability is given in Equation (3).

$$\mathrm{SP}_{c,b,g,y,s} = Y_{c,b,y,g,s} \times A_{b,y,s}, \tag{3}$$

SP = supply potential (GJ) of the selected bioenergy crop *c*, of biome *b*, for grid cell g, at year *y* for the selected yield scenario *s*. *Y* = yield (GJ/ha) of bioenergy crop *c*, for biome *b*, at year *y*, for grid cell g, at year *y* for the selected yield scenario *s*. *A* = area (ha) of biome *b*, at year *y*, for the selected yield scenario *s*.

3.5 | Scenarios

The TIMBRA model is used to assess the impact of GHG emissions on the demand for bioenergy in a Brazilian low-carbon energy system across five scenarios: a reference scenario (REF) and one scenario per key determining factor (see Table 3 for an overview): low agricultural productivity (AP-L), short TH (TH-S), excluding NS (NS-Ex), and static EFs (EF-S).

For the reference scenario, a default representation is chosen for agricultural productivity, NS, TH, and the bioenergy EF. Agricultural productivity is set to high, the TH is set to 85 years, NS is included and EFs are dynamic. Agricultural productivity is set to high because this allows to explore the differences between the other factors.

TABLE 3 Overview of the scenarios as used in this study, categorized by the parameter sets

Scenario	REF	AP-L	TH-S	NS-Ex	EF-S
Agricultural productivity	High	**Low**	High	High	High
Demand agricultural products[a]	SSP1	**SSP3**	SSP1	SSP1	SSP1
Technological development[b]	Progressive	**Conservative**	Progressive	Progressive	Progressive
Carbon budget[c]	16 Gt CO_2-eq. (for Brazil in the period 2010–2050)				
Time horizon[d]	Long	Long	**Short**	Long	Long
Natural succession	Included	Included	Included	**Excluded**	Included
Bioenergy EF	Dynamic	Dynamic	Dynamic	Dynamic	**Static**

Abbreviations: AP-L, low agricultural productivity; EF, emission factor; EF-S, static EFs; NS-Ex, excluding natural succession; REF, reference scenario; TH-S, short time horizon.

Bold scenario settings are parameter changes, compared to the settings of the reference scenario.

[a] The demand for agricultural products is based on the shared socio-economic pathway (SSP) scenarios as used in Doelman et al. (2018).

[b] Technological development of energy conversion technologies follows the SSP trajectory as used in Lap et al. (2019).

[c] See Section 3.1.1 for detailed information.

[d] The time horizon is either long (85 years) or short (20 years).

Since climate mitigation is a long-term goal, it is argued that a TH up to 100 years may be appropriate (Fearnside, 2002). Furthermore, the longer TH helps to account for gradual carbon fluxes which can be presented better using a longer time frame (Daioglou et al., 2017). Since NS may potentially play an important role in bioenergy EFs (Kalt et al., 2019), this is by default included for new bioenergy plantations. Bioenergy EFs are set to dynamic, to represent the natural dynamics of LUC emissions.

The differences within the scenarios for the key determining factors are discussed below. To prevent other parameters from influencing the results of that specific scenario, just one key determining factor is changed, rather than the whole set of possible interactions.

3.5.1 | Agricultural productivity

Agricultural productivity is a key driver that influences the supply potential of bioenergy (Gerssen-Gondelach et al., 2015). In this study, two different yield projections are analyzed: high and low. The projections encompass bioenergy crops as well as all major agricultural products. The yields of the bioenergy crops and the major agricultural products for the three scenarios are shown in Appendix S2.

3.5.2 | Time horizon

The bioenergy EF is calculated by dividing the LUC emissions by the BP over the selected TH (see Section 3.4.1 for details). In this study, a 20-year TH and an 85-year TH are used. IPCC (2014) and the EU (European Parliament, 2018) use the short TH because of the supposed lifespan of bioenergy plantation facilities and biofuel policy, while a longer TH is more appropriate for GHG emission mitigation strategies with a long-term emission target (Daioglou et al., 2017).

3.5.3 | Natural succession

Two options for NS are assessed for new bioenergy plantations: inclusion and exclusion. The sequestered carbon (both in soil and living biomass) over the assessed TH for the NV is calculated with the LPJmL model (see Krause et al., 2017, for more information), and is added to the GHG supply curves as an EF component by dividing the carbon by the bioenergy yield (see Section 3.4.1 for detailed information). The sequestered carbon for AAL (and the other biomes) is found in Appendix S5. In this scenario, NS is also excluded for existing sugarcane plantations.

3.5.4 | Bioenergy EFs

The GHG supply curves distinguish between LUC emissions from embedded carbon of clearing NV, gradual emissions from soil carbon stock changes, and bioenergy cultivation (see Section 3.4). The total bioenergy EFs, as shown in Daioglou et al. (2017), are split into the three abovementioned fractions. From these fractions, the LUC emissions from clearing NV (short-term EF) are allocated to the first time slice within TIMBRA. When TMBRA decides to use this biomass from a new bioenergy plantation, these emissions occur directly in that first period. The other two types of LUC emissions occur on a longer timeframe (long-term EF), and occur during the full TH of the bioenergy plantation (see Figure 3). The distinction between short- and long-term EFs is made for each biome. This allows to investigate the differences between

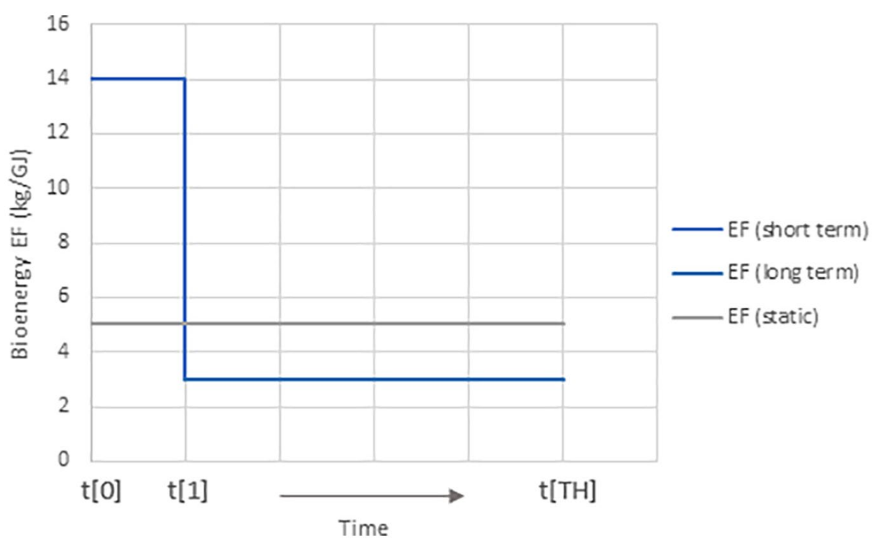

FIGURE 3 Simplified temporal representation of static bioenergy EFs (grey line) and dynamic bioenergy EFs (combination of the blue lines). The total EF over the entire time horizon of both the static and the dynamic EFs is the same. EF, emission factor

the biomes. To investigate the impact of dynamic EFs, the results are compared to a model run using static EFs.

4 | RESULTS

The results are shown in two different sections. The first section focuses on the interaction between the supply of low-carbon bioenergy and the demand, in relation to the scenarios. The second section focuses on the tradeoffs in the energy system with respect to variable demand for bioenergy.

4.1 | Demand for biomass

4.1.1 | General findings

The demand for bioenergy from new bioenergy plantations range from 0.5 to 6.7 EJ in 2050, dependent on the scenario (Figure 4). The differences between the scenarios are large, not only in demand for bioenergy, but also the growth in demand over time and in the associated LUC emissions. The main reason for these differences is the interaction between CO_2 restrictions from the carbon budget that becomes more stringent toward 2050, bioenergy LUC emissions, their dynamics over time, and the demand for low-carbon energy.

From new bioenergy plantations, there is demand for bioenergy with an EF below 15 kg CO_2/GJ, with the low TH scenario as an exception. The associated low-carbon supply potential ranges from 0 to 159 EJ in 2050 dependent on the scenario (see Appendix S3). Although in most scenarios, there is a significant higher supply potential with a similar EF from new bioenergy crops, this potential is not fully utilized because the demand for low-carbon energy is lower, and because of the carbon budget. In 2050, the annual emissions that are allowed within the budget, are just 5% of the emissions in 2015. Bioenergy plantations come with GHG emissions. Even when GHG emissions related to carbon stocks (soil and aboveground biomass) are small, those related to fertilizer application and fuel use for harvest and transport of the biomass still occur. As the total demand is in the order of exajoules, the absolute amount of emissions is also large and forms a significant proportion of the allowable emissions in 2050.

The dynamics of short- and long-term emissions over time is also visible in Figure 4. In general, LUC emissions peak around 2030, due to high short-term EFs from clearance of NV, and stabilize toward 2050. In 2050, the CO_2 emissions from new bioenergy plantations peak in 2030 with a maximum of 150 Mt CO_2 for the low agricultural productivity scenario. After 2030, they decrease and level off to 15%–20% of the peak, with exceptions for the NS and EF scenarios (see below for explanation).

The potential for existing energy crops and residues differ per scenario (see Appendix S3 for details). In general, the demand grows until 2040 for both sources. However, in the final years toward 2050, demand for soybean oil and residues (other than sugarcane straw) decrease drastically, and demand from existing energy crops remain around the same level as in 2040. Especially soybean oil and residues (other than sugarcane straw) are seen as transition fuels. They have a better GHG performance than fossil fuels, but when the carbon budget becomes stringent, other low-carbon sources substitute them, such as hydrogen (from solar energy and wind energy).

4.1.2 | Influence of key determining parameters

Agricultural productivity

The difference in demand for bioenergy is not directly visible when comparing the reference scenario (with high agricultural productivity) to the low agricultural productivity scenario (see Figure 4b). A small decrease in demand is visible, mainly because of less productive energy crops. The major difference between those two scenarios is in the supply potential of abandoned agricultural land. The supply potential from AAL in the category below 15 kg CO_2/GJ is 71 EJ for the reference scenario, compared to 8 EJ when the agricultural productivity is low (Appendix S3).

Although there is low-carbon supply potential on AAL in the reference scenario, this is not utilized. That is because of its long-term emissions, mainly consisting of forgone emissions from NS. Because these forgone emissions occur during the entire TH (the new NV—and its embodied carbon—continuously grows), the total LUC emissions of bioenergy from AAL are relatively high on the long term, in comparison to bioenergy from NV (which have their carbon penalty right after the clearance of the NV). As the carbon budget is stricter toward the end of the TIMBRA modeling horizon, bioenergy from AAL is less attractive as a low-carbon energy source in comparison to bioenergy from NV. Mainly because the spike in LUC emissions from initial clearance happens earlier in time, when the carbon budget is less strict, compared to relatively high emissions from embodied carbon throughout the longer TH, when the carbon budget becomes more strict.

Time horizon

With a TH of 20 years, the demand from new bioenergy plantations is below 0.5 EJ in 2050, significantly lower than the 4.7 EJ in the reference scenario (see Figure 4). High bioenergy EFs cause this low demand. The major

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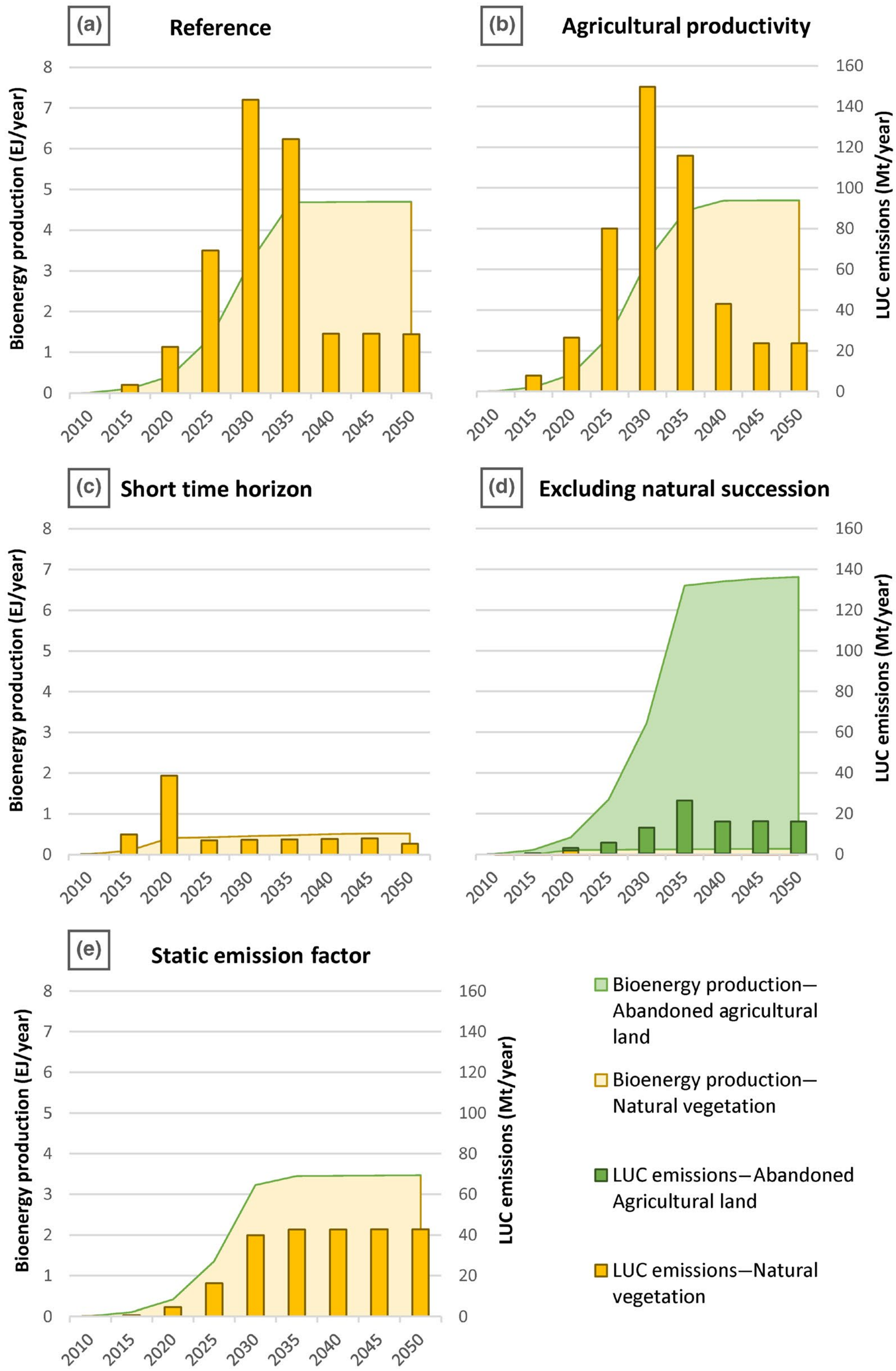

FIGURE 4 Bioenergy production (the solid areas, left axis) and its associated GHG emissions (bars, right axis) from new bioenergy plantations for the period 2010–2050, shown for the five scenarios. Scenario (a) Reference, (b) Agricultural productivity, (c) Low time horizon, (d) Excluding natural succession, (e) Static emission factor. GHG, greenhouse gas; LUC, land-use change

share of that biomass had an average EF between 15 and 20 kg CO_2/GJ. The total LUC emissions from new bioenergy plantations in 2050 reach to 5 Mt in 2050. This small share of biomass is regarded as a cost-effective GHG mitigation option for sectors which are difficult to decarbonize with other low-carbon alternatives.

Natural succession

The effect of forgone emissions from NS is visible in the long-term EF of bioenergy from abandoned agricultural land. When excluded, the demand for bioenergy from abandoned agricultural land reaches 6.7 EJ in 2050 (Figure 4d). The demand for bioenergy is doubling from 2030 to 2050, apart from all other scenarios where the demand is levelling off after 2030. This is related to the fact that there are just marginal short-term emissions, since no NV needs to be cleared, in combination with the absence of forgone emissions from NS which leads to low long-term emissions, basically only from the cultivation of the sugarcane.

The average carbon sequestration due to NS on abandoned agricultural land ranges from 80 to 125 t C/ha, dependent on the agricultural productivity (see Appendix S5). This leads to an EF of NS of 8–13 kg $CO_2/GJ_{bioenergy}$. This highlights the fact that the supply potential from abandoned agricultural lands is not utilized when NS is included, because this would lead to high forgone emissions toward 2050.

Dynamic EFs

When static EFs are used, in comparison to the dynamic EFs in the reference scenario, the demand for bioenergy is lower in 2050 with, respectively, 3.5 and 4.7 EJ (see Figure 4e). This is related to the fact that emissions from the initial clearance of the NV are attenuated over the entire TH, ultimately resulting in higher long-term EFs. Due to an increasingly stringent carbon budget toward 2050, the demand for biomass from new bioenergy plantations is tempered in the static EF scenario.

Another effect of dynamic EFs is that utilization of new bioenergy plantations happens earlier, compared to similar model runs with static EFs, since the carbon budget is less strict at those times which allows a high spike in LUC emissions from clearing NV.

4.2 | Final energy

4.2.1 | Final energy and costs

The final energy mix in shown in Figure 5, per prime energy carrier and per sector. Biomass is mainly consumed in both the transport sector and in the industry, and is the largest energy carrier. The variety between scenarios is small as the total final energy consumption reaches around 12–15 EJ in all scenarios. When a short TH is used, the bioenergy consumption is lower in the transport sector in comparison to the other scenarios, and less hydrogen in the industry. This is compensated by consuming more electricity in those sectors, and slightly more fossil fuels in the industry. In the scenario without NS, more biomass is used to fulfill energy demand in the transport sector. This leads to less use of electricity and hydrogen in the transport sector. The lower final energy use in both the TH and EF scenario is because the conversion efficiency of electricity and hydrogen per unit of energy is higher than bioenergy.

The annual costs of the energy system for 2050 range between 361 and 389 bn $, with the lowest cost related to the case that excludes NS while all other explored cases are

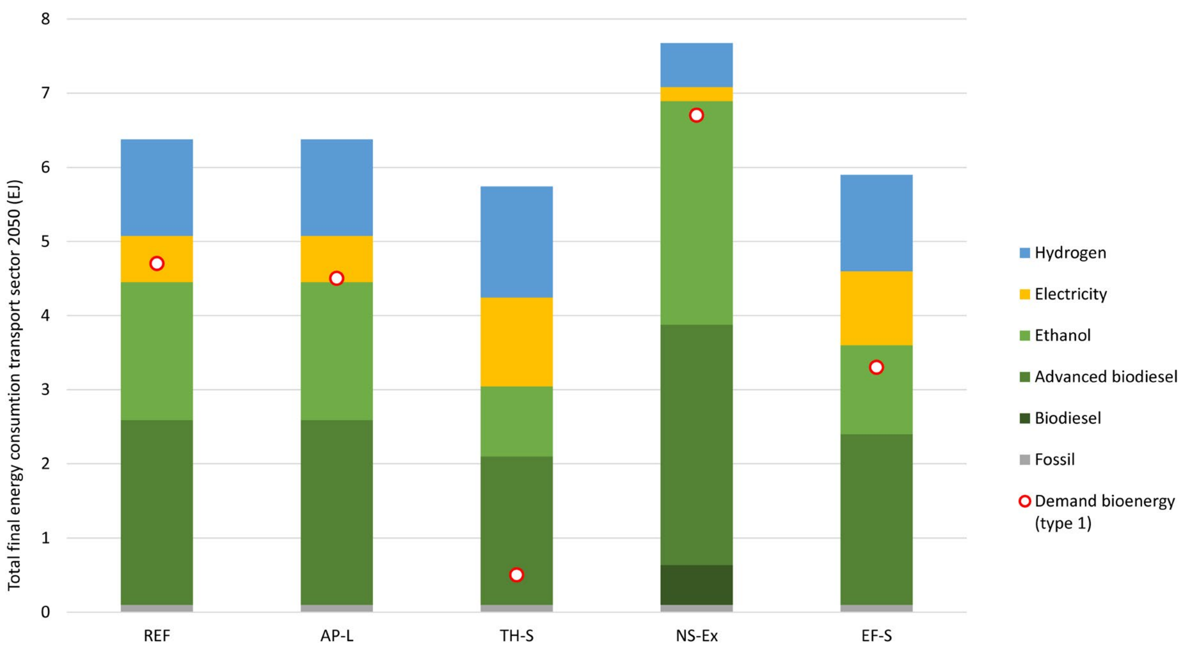

FIGURE 5 Total final energy consumption in 2050 for Brazil per sector and prime energy carrier. Biomass encompasses all three types of feedstock. AP-L, low agricultural productivity; EF-S, static emission factors; NS-Ex, excluding natural succession; REF, reference scenario; TH-S, short time horizon

above 380 bn \$. The difference in costs between excluding NS and the other cases is due to the use of biomass. Higher shares of biomass lead to higher supply costs, but less additional costs are required to produce additional electricity and hydrogen for the transport sector. The latter rise significantly and lead to substantial higher costs.

Bioenergy carbon capture and storage (BECCS) is present in all cases. The full storage potential for storing carbon below the subsurface is utilized by captured CO_2 from bioenergy, rather than from fossil origin.

4.2.2 | Transport sector

The general trend shows that when less low-carbon biomass is available, electricity for private transportation and hydrogen (from electrolysis of solar and wind energy) for freight transport become low-carbon alternatives to meet the transport demand (Figure 6). The preferred order to fulfil the demand for passenger transport with a low-carbon profile is (1) bioenergy (both for passenger and freight transport), (2) passenger transport by electric vehicles, and (3) freight transport on hydrogen. When biomass demand is at its lowest (0.5 EJ in the low TH scenario), one-third of the final demand is supplied by hydrogen and electricity, while this is just 10% in the scenario without NS with demand for bioenergy of over 7 EJ.

Differences per transport mode also occur. In the majority of the scenarios, buses run with ethanol and/or renewable diesel, while electric buses enter the market in the short TH scenario. For freight transport, in the scenario without NS still a share of the trucks drive on biodiesel. Since there is abundant low-carbon bioenergy, no further investments are done to use the biodiesel in a more efficient (but more expensive) way. In that scenario, the same effect is noticed for private transportation as ethanol is the main fuel for cars, and no investments need to be made for more expensive electric cars.

4.2.3 | Power sector

Next to the transport sector, the power sector is also affected by the impact of LUC emissions of biomass production. When the supply potential of low-carbon biomass becomes scarce, hydrogen and electricity are used as low-carbon alternatives to meet transport demand. While electricity is directly consumed by electric cars, hydrogen is produced from electrolysis of renewable electricity. The additional electricity production to meet the demand for electric cars and hydrogen ranges from 660 to 870 TWh in 2050. In comparison to the total electricity demand for the other sectors (1200 TWh), this additional demand requires 56%–75% more electricity in 2050. This additional electricity production is delivered with offshore wind, utility scale PV parks, and concentrated solar power.

Although electric cars and hydrogen trucks form a relative small share in the transport sector (see Figure 6), the effects on the future power sector are large. Decarbonization of the industry and transport sector based on low-carbon electricity will require extensive expansions within the power sector.

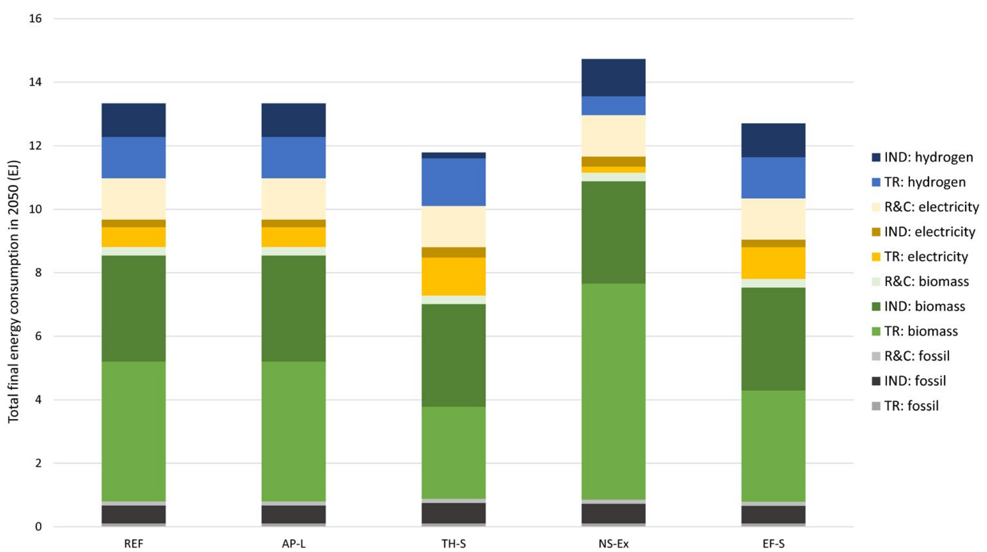

FIGURE 6 Relation between bioenergy demand in 2050 from new bioenergy plantation (EJ) on the right axis (in red white dots) and the total final energy consumption in the transport sector for 2050 per fuel type (EJ) on the left axis. AP-L, low agricultural productivity; EF-S, static emission factors; IND, industry; NS-Ex, excluding natural succession; R&C, residential and commercial; REF, reference scenario; TH-S, short time horizon; TR, transport

On average, the total electricity is produced from burning biomass in a combined cycle power plant with carbon capture facilities (BIGCC-CCS) is 250 TWh. Apart from its cost-effective GHG mitigation, this option is selected because it provides a baseload power production, which is required for grid stabilization to balance the variability of solar and wind energy. In the scenario with a low TH (50 TWh), and for the scenario excluding NS (no production) BIGCC-CCS plays a limited role, mainly because low-carbon bioenergy is very limited available and more suitable as decarbonization option in other sectors (THL scenario), or there is abundant low-carbon bioenergy available and BIGCC-CCS is not an cost-effective GHG mitigation option (NSE scenario).

Intensification of cattle farming is mentioned as a prime solution to reduce GHG emissions from deforestation of the Amazon (Cohn et al., 2014). However, it remains uncertain if high yield projections will lead to a decrease in the total agricultural area. Past records show that yield increase in the Cerrado biome did not result in a reduction of total agricultural area (Goulart et al., 2016). The correct implementation of agricultural policy, aiming at increasing the intensity of beef production, by means of the Forest Code, has shown that deforestation can decrease (Phalan et al., 2016). Full implementation, and strict compliance of the Forest Code (Câmara et al., 2015), and policy aiming at increasing agricultural productivity are necessary to reduce LUC emissions (Garrett et al., 2018).

5 | DISCUSSION

5.1 | Key determining factors

5.1.1 | Agricultural productivity

The results of this study show that high yield projections do not necessarily lead to higher demand for bioenergy. Although abandoned agricultural land is often regarded as promising options to cultivate biomass for BP, without the carbon penalty from clearing NV (e.g., by Fargione et al., 2008), the effect of including NS leads to higher forgone emissions on the long term. However, high yield projections have the potential to free agricultural land with high low-carbon supply potential of bioenergy. When NS is excluded, BP on abandoned agricultural land shows to be a cost-effective low-carbon source, which is preferred above lands with NV.

The demand for agricultural products and technological development have little impact on the final results. Demand for agricultural products influences the availability of agricultural residues, but the use of this bioenergy source is limited because of its EF. Additionally, in the SSP3 pathway, the demand for animal products is higher in comparison to the reference SSP1 pathway, leading to differences in abandonment of agricultural land. In the shown scenarios, this factor is not of influence on the results, because the bioenergy supply potential on AAL is unused because of NS (see Section 4.1.2 for details). However, in the scenario excluding NS, AAL is used. Thus, an SSP3 pathway with higher demand for animal products will reduce the low-carbon supply potential of AAL. Low technological development has negligible effects on the results, as it results in slightly higher system costs because of more expensive and less efficient conversion technologies.

5.1.2 | Time horizon

For calculating bioenergy EFs, acknowledged institutions like the IPCC and the European Commission recommend the use of a 20-year TH. The results of this study show that this affects the supply potential of low-carbon bioenergy substantially. However, when the penalty of the lost carbon stocks (soil- and living biomass) due to land conversion is fully accounted to the 20-year period, after that period the GHG savings from these lands can be very high as only the emissions related to the cultivation and transportation of the biomass are incorporated in the bioenergy EFs. As our results show that there is demand for bioenergy with a short TH, on the longer run the GHG savings can be much higher beyond 2050. Moreover, as mitigating climate change is a long-term effort, the use of a longer TH for calculating EFs may be reasonable (Fearnside, 2002).

In life cycle assessments, quantification to a single EF requires a chosen TH. However, this single EF can be perceived as real-time emissions that occur constant over the chosen TH, which deviates from reality. When incorporating real-time emissions (though modeled estimates), there is no need to define a specific TH for biomass from new bioenergy plantations, because the dynamic fluxes of LUC emissions are incorporated.

5.1.3 | Natural succession

Natural succession can be perceived as a GHG mitigation option as it accumulates atmospheric carbon and fixes it into the biomass. However, the buildup of carbon stocks of NS will slow down, and on the long run it will reach an equilibrium stage. There is also the risk that this sequestered carbon is lost due to fires, diseases, and other land-use claims. In comparison to carbon savings from replacing fossil fuels with biofuels, carbon savings from NS will fade out on the longer run making it less suitable as a GHG mitigation option since mitigating global warming is a long-term goal (IPCC, 2014). Furthermore, as NS can be seen as reforestation, it is related to AFOLU mitigation options. Therefore, it should be assessed in competition with similar mitigation options to assess its potential as a climate mitigation option. This requires a different methodology that can assess land-use-related mitigation options in combination with energy-related mitigation options.

This study highlights the importance of NS as a bioenergy EF component. Assuming that NS will occur when land is spared from an ecological perspective true. However, the drivers that will influence land sparing are much more complex, especially if GHG mitigation via land systems is incentivized. Yield increases happen as a result of demand for food, and a shortage of fertile land. The assumption that spared land is simply a result of continuous yield increase, does not do justice to the complexity of this problem, because only with demand for bioenergy, yield improvements that make land available actually take place. From a modeling perspective, defining a new counterfactual scenario might solve this issue. In this new NV case, no agricultural land is assumed to be freed from agricultural production. Agricultural productivity is likely less intensive in comparison to the bioenergy case. The new bioenergy scenario should account for increasing GHG emissions (because of higher GHG emissions due to more intense land use), but NS can be excluded as an EF component of bioenergy plantations.

The complexity around GHG mitigation options using terrestrial ecosystems, in relation to low-carbon energy demand, requires more research. A potential interesting approach would be to analyze stakeholder behavior (especially farmers and forestry companies) by agent-based modeling, as also discussed by Meyfroidt et al. (2018). By doing so, analyses can be made whether stakeholder intensify their agricultural activities, and spare parts of their own agricultural land for BP and/or reforestation to mitigate GHG emissions.

5.1.4 | Dynamic EFs

Modeling bioenergy with dynamic EFs comes closer to the real situation as the dynamic nature of GHG emissions from LUC is incorporated. The results show that there is a clear relation between starting-up plantations, its related LUC emissions and carbon constraints, especially from a temporal point of view. Not only the timing is elucidated, the demand for bioenergy is also affected. By using dynamic bioenergy EFs, improvements can be made in assessing the potential for bioenergy. While some policies depend on static EFs for bioenergy (e.g., the RED II of the European Union, European Parliament, 2018), the use of dynamic EFs, in combination with integrated land- and energy system modeling, might result in better bioenergy deployment estimates.

5.2 | Model improvements

5.2.1 | GHG supply curves

The use of LPJmL for deriving the GHG supply curves has some limitations. First of all, one particular energy crop needs to be selected. In reality, a particular site might be more suitable for a different energy crop. Second, the model assumes that the production of both food and energy takes place in the most suitable location. The suitability is mostly based on biophysical conditions. However, socio-economic conditions also affect land allocation to a large extent (Verstegen, 2016). Third, a “food-first” principal is applied assuming that new bioenergy plantations will not be produced on agricultural land. In practice however, this can be different. Past sugarcane expansions replaced mainly pasture lands (Adami et al., 2012), which potentially caused indirect LUC. Fourth, the spatial resolution of this study is rather coarse in comparison to, for example, PLUC (Verstegen, 2016), leading to uncertainty in the modeling results (Panichelli & Gnansounou, 2015). Fifth, the calculations of the EFs related to bioenergy cultivation are assumed to be constant over time. Therefore, emission reduction options for fuel use for machineries, chemicals, and artificial fertilizers are not part of this assessment. Including those options (e.g., drop-in biofuels to meet agricultural fuel demand and ammonia from biomass) can result in lower EFs for bioenergy. Furthermore, the GHG supply curves can provide more detail once gridcell-based raw data can be used in energy system models, leading to a smoother GHG–supply curve. Improvements spatial visualization and separation of EF components can result in more accurate modeling results, and better understanding of the raw data which, in turn, can lead to improvements of the overlying models as well.

In summary, the used methodology is a stylized representation of land allocation with limitations. Though this is appropriate for the aim of this study, it is not ideal to study LUC in detail. More detailed land-use allocation models like PLUC (Verstegen et al., 2014) or CLUE (Verburg & Overmars, 2009) are more appropriate, although the higher resolution may be unsuitable for precise projections over a longer time frame (Verstegen, 2016). To cross-check the results from this study, the demand for bioenergy, as calculated in this study, can be used as input for detailed land allocation models. By doing so, the deviation between direct and indirect LUC can be observed and a comparison can be made between LUC emissions based on suitable locations versus more realistic locations.

5.2.2 | Carbon budget

The selected carbon budget in this study is devoted to the GHG emissions only from the energy sector. As Rochedo et al. (2018) show, the total budget (between 2010 and 2050) for Brazil is estimated to be around 23 Gt CO_2 for the entire country, and the uncertainty related to that value is rather high. This implies that the budget chosen here might be too strict. However, as the LUC emissions related to the production of biomass for bioenergy can be linked directly to the production of energy, it is fair to link it to that budget. Additionally, the main drivers behind AFOLU emissions in Brazil are in general not directly linked to BP, but rather to the beef industry (both cattle farming and feed production from soybeans) (Nepstad et al., 2014), while also illegal logging (Azevedo et al., 2017) and mining activities (Sonter et al., 2017) cause deforestation.

A different choice in the carbon budget would have led to different results. A lower carbon budget would have led to less demand for bioenergy, and demand would rise when the carbon budget was higher. However, the low-carbon supply potential is already limited in most scenarios. Therefore, the results would have been amplified, but the trends would not have differed drastically.

5.2.3 | AFOLU mitigation options

The focus in this study is on the production of bioenergy for climate mitigation. However, afforestation can also result in carbon savings. The incorporation of afforestation as a GHG mitigation option within an energy system model requires a different methodology that focuses on the forestry sector and its dynamics, like, for example, the MESSAGE-GLOBIOM model (Havlík et al., 2011). Furthermore, growth in carbon stocks due to afforestation happens usually over a long period. It is difficult to assess this long-term mitigation from growing carbon stock within the platform of an energy system model (Köberle, 2018).

5.2.4 | Export

In this study, the export of bioenergy is not included. It should be noted however that GHG mitigation strategies for countries with low biomass potential advocate to use imported biomass to fulfil their own GHG mitigation strategies. Brazil is often mentioned as major exporting region of bioenergy. Daioglou et al. (2020) evaluated international bio-energy trade across eight IAMs in scenarios consistent with the Paris Agreement. The demand for Brazilian bioenergy to reach those targets varies between the models, ranging from 0 to 30 EJ of primary biomass per year. On top of the domestic demand for bioenergy, the total demand can reach nearly 50 EJ. Given the scenario excluding NS, it might be possible to supply this quantity with low associated GHG emissions. However, if this is not the case exporting 30 EJ may lead to high LUC emissions.

5.2.5 | Crop choice

Although sugarcane is often highlighted as the energy crop with the highest potential, other crops can also yield substantial amounts of energy. The analysis as shown here is also performed with two different crops: eucalyptus and miscanthus. More details are shown in Appendix S4. The trends between the scenarios are comparable, although eucalyptus yields are nearly half of those of sugarcane, and miscanthus is two-third of sugarcane. In some circumstances, miscanthus shows a higher low-carbon supply potential. This indicates that specific locations are favorable for miscanthus.

The demand for bioenergy from new sugarcane plantations is substantially higher (see Figure A3-1 in Appendix S3) than for the other crops. The reason for this is not only a higher supply potential, but also that the sugarcane industry is a mature industry that exists already. Since advanced bio refineries (converting lingo-cellulosic biomass to advanced biofuels) are expected to phase in around 2040 their GHG mitigation potential is limited to the relative short period 2040–2050. This especially because sugarcane ethanol options are so competitive when combined with BECCS, resulting in negative emissions. This is also the period where carbon restrictions become most stringent. These restrictions result in limited selection of supply potential with lower EFs from eucalyptus and miscanthus, since they are still causing (limited) GHG emissions.

5.3 | Final remarks

This study aimed to show how LUC emissions can influence the demand for bioenergy as an option for climate change mitigation, and how this affects national final energy consumption. Furthermore, it evaluates the effect of key parameters that affect the EFs and the supply potential of biomass.

The demand for biomass is mainly influenced by its associated EFs. While there is a relative high supply potential for biomass with an average EF above 15 kg CO_2-eq./GJ, the demand for this biomass is negligible. Although supply potential between 0 and 15 kg CO_2-eq./GJ is relatively small, still the demand remains small, meaning that other low-carbon options to fulfill demand for energy are more cost-competitive. The low-carbon demand for biomass from new bioenergy plantations range from 0.5 to 6.7 EJ in 2050.

Natural succession plays a key role in demand for bioenergy. When excluded, this demand is 6.7 EJ in 2050, compared to 5.2 EJ when included. High agricultural productivity is a pre-requisite to spare agricultural land. Inclusion of NS on those lands leads to relatively high long-term emissions due to forgone carbon sequestration in NV, compared to bioenergy produced on land with NV that have a high carbon penalty directly at the start due to clearing the NV. Exclusion of NS as an EF component from bioenergy produced on abandoned agricultural lands results in high supply potential with low associated GHG emissions. The assumption that spared land is simply a result of continuous yield increase (which is the reason to include NS as an EF component) does not do justice to the complexity of this problem, because only with demand for bioenergy, yield improvements that make those lands available actually take place.

Using dynamic instead of static EFs influences the timing of new bioenergy plantation as well as the demand for bioenergy. This is mainly caused by the interaction between dynamic LUC emissions and carbon constraints that become increasingly stringent toward 2050. The results show that LUC emission peaks around 2030 due to clearance of NV, before leveling off to 2050. In the static EF scenario, a more gradual trend is where LUC emissions top in 2050. The attenuated emissions due to clearance of NV result in a higher EF in 2050, in comparison to the reference scenario with dynamic EFs. Due to an increasing stringent budget in 2050, there is less demand for bioenergy in the static EF scenario (3.5 EJ), compared to the reference scenario (4.7 EJ).

When low-carbon bioenergy demand from new bioenergy plantations is below 1 EJ, on average 33% of the transport energy demand is supplied by a mixture of electricity and hydrogen. Under limited low-carbon biomass availability, electric vehicles become a cost-competitive low-carbon alternative for passenger transportation. Hydrogen (produced from electrolysis of renewable electricity) is seen as a cost-competitive alternative for freight transportation. The demand for electricity for electric transportation and hydrogen production for the industry reaches on average 720 TWh, an additional growth in demand for electricity of 62% in comparison to the standard demand. This can lead to a 12% increase in the overall costs of the energy system. The increase in low-carbon electricity production, as shown in this study, is likely to cause problems, with, for example, transmission grid planning (Barbosa et al., 2017), grid stability (Lap et al., 2020), and social acceptance (Brannstrom et al., 2017), and will lead to higher costs compared to energy systems with a larger share of bioenergy (Lap et al., 2020).

While low-carbon energy might serve as a cost-effective GHG mitigation option, producing low-carbon bioenergy should come with a set of restrictions that need careful consideration. Mechanisms should (1) incentivize and protect production over a long TH, (2) carefully selected locations, (3) induce bioenergy producers to show their GHG performance, and (4) allow for independent monitoring of GHG performance. Furthermore, strict policies like, for example, land zoning should be implemented to sustain valuable ecosystems, and provide insight in potential locations for BP. More research is needed to guide policymaker for concrete implementation of alike measures, which requires integrated modeling studies to understand the complexity between land and energy systems, and their economic and societal relations.

Bioenergy demand projections, as calculated in this study, can be used as input for land-allocation models to study spatial allocation, and subsequent LUC emissions in more detail. These land-allocation models can help to understand the interaction between land demand, spatial allocation, and LUC. Thereafter, results from these land-allocation models can be used to refine low-carbon bioenergy supply potential as used in energy system optimization models. Next, Brazil is seen as a potential export region for biofuel. By including export in this methodological framework, the effects on the domestic energy system can be explored, and the emission profile of the exported bioenergy can be assessed.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the Supporting Information of this article.

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