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Advancing life cycle assessment of bioenergy crops with global land use models

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Abstract

Bioenergy crops can cut greenhouse gas (GHG) emissions, yet often bring hard-to-quantify environmental impacts. We present an approach for integrating global land use modeling into life cycle assessment (LCA) to estimate effects of bioenergy crops. The approach involves methodological choices connected to time horizons, scenarios of GHG prices and socioeconomic pathways, and flexible data transfer between models. Land-use change emissions are treated as totals, avoiding uncertain separation into direct and indirect emissions. The land use model MAgPIE is used to generate scenarios up to 2070 of land use, GHG emissions, irrigation and fertilizer use with different scales of perennial grass bioenergy crop deployment. We find that land use-related CO_2 emission for bioenergy range from 2 to 35 tonne TJ^{-1}, depending on bioenergy demand, policy context, year and accounting method. GHG emissions per unit of bioenergy do not increase with bioenergy demand in presence of an emission tax. With a GHG price of 40 or 200 \$ tonne^{-1} CO_2, GHG per bioenergy remain similar if the demand is doubled. A carbon tax thus has a stronger effect on emissions than bioenergy demand. These findings suggest that even a relatively moderate GHG price (40 \$ tonne^{-1} CO_2) can prevent significant emissions, highlighting the critical role governance plays in securing the climate benefits of bioenergy. However, realizing these benefits in practice will depend on a coherent policy framework for pricing CO_2 emissions from land-use change, which is currently absent. Overall, our approach addresses direct and indirect effects associated with irrigation, machinery fuel and fertilizer use as well as emissions. Thanks to a global spatial coverage and temporal dimension, it facilitates a systematic and consistent inclusion of indirect effects in a global analysis framework. Future research can build on our open-source data/software to study different regions, bioenergy products or impacts.

1. Introduction

Bioenergy is both high-profile and controversial as a potential key option to mitigate climate change. Unlike other renewable energy but like fossil energy, bioenergy is a combustible energy form and can be easily transported and stored. Biofuels can substitute fossil fuels in aviation, shipping and other sectors where electrification is challenging (Cavalett and Cherubini 2022, Luderer *et al* 2022) and, if successfully combined with carbon capture and storage, deliver negative CO_2 emissions (Fajardy and Mac Dowell 2017, EASAC 2018, Field *et al* 2020).

At the same time, there are concerns that bioenergy crops can compete with food production and exacerbate issues connected to water and land scarcity (Smith *et al* 2015, Heck *et al* 2018, Humpenöder *et al* 2018, Naomi *et al* 2018, Luderer *et al* 2019). Another concern is emissions associated with biomass feedstocks, which includes releases of CO_2 by vegetation and soil directly or indirectly caused by land use, N_2O emissions related to fertilizers and fossil fuel emissions in supply chains (Tonini *et al* 2016, Staples *et al* 2017, Kwon *et al* 2021).

Several families of tools have been used for assessing environmental aspects of bioenergy crops, including land use management models, life cycle assessment (LCA), economic (partial) equilibrium models, energy system models and integrated assessment models (Jeswani *et al* 2020, Welfle *et al* 2020, Calvin *et al* 2021, Escobar and Laibach 2021, Xu *et al* 2022). Distinctions between model groups are not always clear. For example, integrated assessment models frequently incorporate global land use models in their full or reduced form (Harfoot *et al* 2014, Wise *et al* 2014, Stehfest *et al* 2019), and LCA can be coupled with economic equilibrium modelling (Searchinger *et al* 2008, Dandres *et al* 2011).

In the LCA community, the way to represent emissions indirectly induced by bioenergy land use—often termed indirect land use change (ILUC) emissions—has been widely debated (Ahlgren and Di Lucia 2014, Finkbeiner 2014, Schmidt *et al* 2015). ILUC emissions occur when bioenergy crops displace crops elsewhere and ultimately lead to expansion of agricultural land at expenses of natural land. ILUC estimates vary substantially depending on the type of biomass, assumed context and approach (Wicke *et al* 2012, Ahlgren and Di Lucia 2014). For example, one case study finds that uncertain choices pertaining to land representation attributes in a bioenergy land use change model change estimated emissions by 20%–30% (Plevin *et al* 2022). Over the years, improvements in methods have reduced medians or means of ILUC estimates, from more than 100 tonne $CO_2e\ TJ^{-1}$ to less than 10 tonne $CO_2e\ TJ^{-1}$ (Wicke *et al* 2012), but without reducing inherent uncertainty (Zilberman 2017, Daioglou *et al* 2020). This uncertainty calls for further development of approaches and new investigations to help improve ILUC estimates and understanding of emission implications of bioenergy land use.

Furthermore, many previous ILUC studies are limited in that they assume a biofuel demand for a given region and given year to compute ILUC factors, while in reality, biofuel demand, emission fluxes and relationships between the two will vary across time and space. Approaches that couple LCA and global land system models can potentially overcome this limitation because global land use models consider total emissions from land use changes so that all emissions become direct and the conundrum of ILUC that relies on artificially constructed boundaries in time and space is avoided. Examples of global land system model are MAgPIE (Dietrich *et al* 2019), the GCAM agriculture and land use model (Wise *et al* (2014) and GLOBIOM (Havlík *et al* 2014), which simulate future land systems in response to given sets of assumptions and mechanisms. Such models are used standalone or coupled with energy-economy models in integrated assessment model (IAM) model frameworks (Popp *et al* 2017, Rose *et al* 2020).

The aim of this research is to outline and test an approach for integrating scenarios from global land use modelling into LCA to estimate direct and indirect effects of large-scale bioenergy crop production. The approach allows for incorporating global land use dynamics into LCA in scenarios reflecting different assumptions, for example in terms of the shared socioeconomic pathways (SSPs) (O'Neill *et al* 2014, Popp *et al* 2017), governance of emissions from land use, or whether bioenergy crops are irrigated or not. This is achieved by defining a set of scenario dimensions to be analysed, and then by systematically feeding parameter values from the land use modelling–such as fertilizer use, water irrigation, and land use-related emissions–into the LCA. Rather than singling out an ILUC factor based on a static snapshot and/or consideration of a subset of the land use sector as in many previous assessments, the approach deals with total global emissions from all land-use changes (direct and indirect and over time) in a consistent manner and without the need for a distinction between direct or indirect emissions.

We demonstrate the use of the approach through a case study of second-generation grassy bioenergy crops for the years 2030–2070[6], showing scenario LCA results for land occupation, total greenhouse gas emissions and fossil fuel greenhouse gas emissions. Grassy bioenergy crops are chosen because they usually represent the main type of bioenergy feedstock in future scenarios (Rogelj *et al* 2018, Rose *et al* 2020). Besides, compared to conventional crops, perennial grasses (e.g., switchgrass, miscanthus) typically offer advantages such as increased soil carbon storage, avoidance of tillage, capacity to restore degraded land and improved biodiversity (Robertson *et al* 2017, Yang *et al* 2018, Englund *et al* 2020). The case study applies data from the established land use model MAgPIE (Dietrich *et al* 2022), which has provided pathways for SSPs and contributed to several IPCC reports (Popp *et al* 2017, Rogelj *et al* 2018, Smith *et al* 2019, Nabuurs *et al* 2022). We make available data and software

[6] Bioenergy is often divided into first and second generation, where the former refers to bioenergy from food or feed crops and the latter to non-edible plants such as perennial grasses.

that can be built on in future research (Arvesen *et al* 2022; Data availability statement). The software is based on Brightway2 (Mutel 2017), a Python-based tool increasingly employed for prospective LCA (Cox *et al* 2018, Besseau *et al* 2019, Joyce and Björklund 2022, Sacchi *et al* 2019, Sacchi *et al* 2022).

2. Methods

This section describes methods and data used to combine land use modelling and LCA to analyse effects of second-generation grassy bioenergy crops for the years 2030–2070. The chosen time horizon until 2070 aims to strike a balance between understanding potential mechanisms and implications on the one hand, and limiting uncertainties associated with future trajectories on the other hand. The time horizon allows for a sufficiently long-term perspective to address long-term challenges of climate change mitigation and food supply, while maintaining reasonable assessments of mechanisms and effects. Further, land use modelling results to be presented later show a trend of cumulative land use emissions plateauing in most scenarios by 2070; this also adds support for our chosen time horizon.

First, in section 2.1, we present the principles for scenario integration that are considered in our analysis. Section 2.2 then presents an overall description of land use modelling with the model MAgPIE, before section 2.3 details the specific land use scenarios analyzed. Next, section 2.4 treats different options for incorporating land use CO_2 results from land use models into LCA. Last, section 2.5 presents datasets used to carry out scenario-based LCA of grassy bioenergy crops for 2030–2070.

2.1. Principles for scenario integration

Land system model variables may have mixed levels of specificity or aggregation, also within the same model. For example, variables of the land system model MAgPIE differentiate yields of different types of crops. We refer to such variables as 'crop-specific', or just 'specific', variables. Other MAgPIE variables including emissions do not differentiate between crop types. These undifferentiated variables are aggregated to represent the entire agriculture sector, i.e., for example fertilizer use is reported as an aggregated value representative of all crops grown for bioenergy and other purposes (food, feed, fiber). We refer to such variables as 'aggregated' variables.

2.1.1. Crop-specific variables

The most straightforward case of implementing land system model variables in LCA is when coefficients can be derived directly from crop-specific variables representing the average for the crop type in question. For example, in an LCA of grassy bioenergy crops, an LCA coefficient for cropland occupation (in units of km^2-yr PJ^{-1} or similar) can be derived from a specific grassy bioenergy average crop yield (in units of tonne ha^{-1} yr^{-1} or similar)[7]. It is common for land system modules of integrated assessment models to simulate specific crop yield values (Li *et al* 2020), sometimes also distinguishing irrigated and rainfed bioenergy crops (Dietrich *et al* 2019).

Higher precision is an obvious benefit of using specific variables as opposed to aggregated variables. A conceptual limitation is that indirect effects resulting from competition and interplay between different types of agricultural crops are not captured. In other words, combined effects (on fertilizer application, irrigation, etc) for the whole agricultural sector are disregarded. Indirect land use changes and consequent CO_2 emissions cannot be captured, as these effects are inherently related to developments of the whole agricultural sector.

In practice, the availability of crop-specific model variables can be limited. For example, specific variables available from MAgPIE are limited to crop production, area and yield, which in the context of LCA are mainly relevant for land occupation. Thus, if the goal is to integrate scenario information from MAgPIE into LCA, another method needs to be sought.

2.1.2. Differences in aggregate variables

An alternative way of implementing land system model variables in LCA is to calculate differences in aggregated variables between a bioenergy scenario and a zero-bioenergy scenario and let this difference represent net effects of bioenergy. For example, this approach may take land use in the whole agricultural sector in a scenario with bioenergy less agricultural land use in a scenario without bioenergy, and then attribute the net difference to bioenergy. To illustrate with numbers, say that a scenario in a given year has 100 EJ bioenergy production from bioenergy crop type X and total agricultural land use 2000 million ha; while a scenario without bioenergy has 0 production from bioenergy crop type X and total agricultural land use 1700 million ha. This would yield land occupation $(2000 \text{ million ha} - 1700 \text{ million ha})/(100\ EJyr^{-1} - 0\ EJyr^{-1}) = 30\ \text{km}^2 yrPJ^{-1}$. Meanwhile, say that the land use model specifically estimates land occupation for bioenergy crop type X of 25 km^2-yr PJ^{-1} for

[7] It is established convention in LCA to analyze land occupation in units of m^2-yr MJ^{-1}, km^2-yr PJ^{-1} or similar units; see for example Huijbregts *et al* (2017) or Luderer *et al* (2019).

the given year in the scenario with bioenergy. In this example, the land occupation estimate is 5 km^2-yr PJ^{-1} higher with the difference in aggregate variables approach compared to the specific estimate.

In this way, effects are attributed to bioenergy based on a difference in an aggregate variable that represents the land use of the whole agricultural sector. The difference must apply to a given geographical area, which can be the world, as in the case study we will report, or a specific world region. In the latter case, leakage effects need to be monitored; otherwise, they may go undetected. Generally, we do not expect net differences to be negative, but this can occur through indirect routes in the modelled system.

A key benefit of using differences in aggregate variables is that it allows for capturing indirect and market-mediated effects that are relevant for policy and other decision processes, and that cannot be ascertained from specific variables (e.g., land use change and related CO_2 emissions, food crop production causing changes in fertilizer or water demands of food production elsewhere). Further, a practical benefit is the possibility to unravel crop-specific effects in the absence of available crop-specific variables. This can increase the feasibility of using land model scenario data for LCA.

Two potential disadvantages are lower transparency and more difficult results interpretation, relative to when using specific variables. Lower transparency and interpretability will tend to occur because results are subject to competition (market-mediated) effects between different types of crops, for which the underlying mechanisms can be difficult to disentangle. In other words, uncertainty is higher due to the lack of truly detectable cause-effect chains. It is not necessarily straightforward to decompose land system model results into individual mechanisms or components; for example, to distinguish between substitution effects, price-induced changes, and direct land replacement (Daioglou et al 2020).

2.2. Land use modelling

We employ the MAgPIE 4 open-source land-use modelling framework (Dietrich et al 2019, Dietrich et al 2022). MAgPIE combines economic and biophysical approaches to simulate spatially explicit global scenarios of land use and environmental interactions. It is a global partial equilibrium model of the land-use sector that operates in a recursive dynamic mode and incorporates spatially explicit information into an economic decision-making process.

MAgPIE takes regional conditions such as demand for agricultural commodities, technological development, and production costs as well as spatially explicit data on biophysical constraints into account. Geographically explicit data on biophysical conditions (e.g., carbon densities for vegetation, litter and soil, agricultural productivity such as crop yields) are sourced from the LPJmL land model (Schaphoff et al 2018, von Bloh et al 2018, Lutz et al 2020, Herzfeld et al 2021), then aggregated using a clustering algorithm (Dietrich et al 2013).

Land types in MAgPIE include cropland (food, feed, material, and bioenergy), pasture and rangeland, forest (primary, secondary and managed), other land (non-forest vegetation, abandoned agricultural land, and deserts), and urban land. International trade follows historical patterns and economic competitiveness. Food demand is derived based on population growth and dietary transitions, accounting for changes in food waste and intake, with shifting shares of animal calories, processed products, and more. Production is distributed among areas via minimizing production costs[8].

Crop yield increases due to technological change are modelled endogenously based on regionally different investment-yield ratios and interest rates (Dietrich et al 2012, Dietrich et al 2014). Hence, the model simultaneously optimizes yield-increasing technological change and cropland expansion, which is especially relevant for long-term projections.

Bioenergy crop yield patterns are based on LPJmL. Due to the lack of robust data on second generation bioenergy, land-use intensity data from Dietrich et al (2014) is used to calibrate bioenergy yields in MAgPIE. LPJmL bioenergy yields in Europe, consistent with observations from well-managed test sites, are assumed to match the highest observed land-use intensification. Bioenergy yields in other regions are scaled down based on European land-use intensity, with calibration factors of 0.46 for Sub-Saharan Africa and 0.6 for India, reflecting considerable yield gaps compared to best practices. These yield gaps can be closed in MAgPIE in the future due to yield-increasing technological change. Moreover, technological change can also shift the technological frontier.

Annual net CO_2 emissions from land-use change are calculated based on changes in carbon stocks of vegetation, litter and soil. To mitigate single year biases, we calculate an average value by applying a low-pass filter that distributes annual net CO_2 over time (Humpenöder et al 2022). Changes in vegetation carbon stocks

[8] This usually means that highly productive areas are first taken into production and marginal areas last. However, as different production categories (e.g., food and bioenergy) compete for land, it is not always clear what land will be used next when bioenergy production is expanded. In many cases the model will expand into natural vegetation which promises the next highest yield, but in other cases also reshuffling might happen switching areas for bioenergy with areas for food or boosting overall productivity via investments into yield increases (R&D and management).

are subject to land-use dynamics such as conversion of forest into agricultural land. In case of re-/afforestation or when agricultural land is taken out of production, regrowth of natural above ground vegetation removes CO_2 from the atmosphere, but changes in soil organic carbon are not accounted for.

Nitrogen inputs on cropland via industrial and intentional biological fixation, and N_2O emissions from agricultural soils and animal waste management, are estimated using a nitrogen budgets (Bodirsky *et al* 2014, Stevanović *et al* 2017). CH_4 emissions from enteric fermentation, animal waste management and rice cultivation are estimated based on feed demand, manure, and rice cultivation area, respectively (Popp *et al* 2010, Stevanović *et al* 2017). In the case of GHG emission pricing, CO_2 emissions are reduced endogenously through reduced conversion of natural land, while CH_4 and N_2O emissions are reduced based on marginal abatement cost curves.

2.3. Land use scenarios

To be able to examine effects of bioenergy under different conditions, we define a set of scenario assumptions that are inputs to the land use scenario modelling. Three key scenario dimensions are considered: (i) Bioenergy demand (2 variants with bioenergy demand in addition to 1 with zero demand); (ii) shared socioeconomic pathway (SSP) (3 variants); and (iii) greenhouse gas (GHG) price for the land sector (3 variants). These scenario dimensions are varied in the land use modelling to generate a total of $2 \times 3 \times 3 = 18$ individual scenario LCA datasets and associated analyses. The SSPs are a set of five narratives outlining potential pathways for human development and global environmental changes throughout the 21st century; we refer to previous studies for descriptions of their characteristics (O'Neill *et al* 2014, Riahi *et al* 2017). Our scenarios have a more quantitative than qualitative or narrative-based nature, but are linked to the narratives of the three selected SSPs (Popp *et al* 2017), as characteristics of the different SSPs, such as land productivity growth and globalization, are incorporated into the land use modelling.

For this study, endogenous rates of yield-increasing technological change are derived for each of the SSPs using the scenarios with zero bioenergy demand and GHG price. In other scenarios with higher bioenergy demand or GHG price, the corresponding SSP-specific trajectory is used as exogenous input (i.e., rates of change are the same for a given SSP and follow the scenario with zero demand and zero GHG price.

The three scenario dimensions are described in the following.

2.3.1. Bioenergy demand

The present study considers three stylized demands for global second-generation grassy bioenergy crops:

(i) B50: Linear increase in annual demand with 50 EJ yr^{-1} demanded in 2050 (and linear increase thereafter).

(ii) B100: Linear increase in annual demand with 100 EJ yr^{-1} demanded in 2050 (and linear increase thereafter).

(iii) B0: Constant zero (0 EJ yr^{-1}) demand.

The B50 demand is in the lower end of estimates of technical potentials for dedicated biomass production systems (with food security and environmental constraints considered) according to IPCC AR6 (Nabuurs *et al* 2022). The B50 and B100 demands both fall in the low-medium range of bioenergy deployments in IPCC AR6 integrated assessment model scenarios to limit global warming to 2 °C (Riahi *et al* 2022). B50 and B100 are sufficiently different to enable identification of potential non-linear changes in the global land system depending on bioenergy demand.

Note that B50 and B100 scenarios are used as basis for separate LCA datasets. B0, on the other hand, is only used as a reference when employing differences in aggregated variables (i.e., B100-B0 values or B50-B0 values), as explained previously. As the focus of the current study is second-generation grassy bioenergy crop, we assume no future growth in first generation bioenergy.

2.3.2. Shared socioeconomic pathway

The shared socioeconomic pathways (SSPs) reflect different evolutions in socioeconomic factors and are currently an established component in climate change research (Bauer *et al* 2017, O'Neill *et al* 2014, Riahi *et al* 2017). In the context of land system modelling, the choice of SSP can affect food, feed and material demands, trade, interest rates, nitrogen efficiency and water protection (Popp *et al* 2017). By defining LCA data based on scenarios for different SSPs, one can represent such variations in the LCA.

While all available SSPs can be relevant, in this study we select three SSPs:

(i) SSP1: 'Taking the green road'.

(ii) SSP2: 'Middle of the road'.

(iii) SSP5: 'Taking the highway'.

These are chosen here because they span the full range of mitigation challenges portrayed by the SSP framework. We do not pay explicit attention to varying levels of adaptation challenges as most strongly emphasized by SSP3 and SSP4, as adaptation challenges are less relevant for our current purposes.

2.3.3. GHG price

To represent varying degrees of governance of land use change emissions, we apply a varying price to CO_2 emissions from deforestation and other changes in natural vegetation. With this approach, the scope of forest protection policy is not explicitly defined but is implicitly represented through the CO_2 price. It is important to note that all CO_2 emissions from land-use change, whether directly or indirectly caused by bioenergy crop cultivation, are subject to pricing. To simplify, we treat afforestation separately based on existing policies, omitting any CO_2 price-induced afforestation from the modelling.

Specifically, we consider three CO_2 emission price trajectories ('T' denotes 'tax'):

(i) T200: Linear increase with 100$ t^{-1} CO_2 in 2030 and 200$ t^{-1} CO_2 in 2050.

(ii) T40: Linear increase with 20$ t^{-1} CO_2 in 2030 and 40 t^{-1} CO_2 in 2050.

(iii) T0: Constant zero (0) CO_2 price.

We also price CH_4 and N_2O emissions from agriculture based on these CO_2 price trajectories. We convert CH_4 and N_2O to CO_2-equivalents using IPCC AR5 100-year global warming potential (GWP) conversion factors of 28 and 265, respectively.

2.4. Time dynamics for land use CO_2 emissions

Among the outputs of land use modelling, land use change and consequent CO_2 emissions tend to be particularly subject to temporal variations. Unlike fertilizer use, N_2O emissions, irrigation, etc that occur continuously with bioenergy production, land use changes and CO_2 emissions are typically dominated by one-time land use change events. Based on this rationale, we present three options for determining LCA coefficients for land use-related CO_2 (in units of tonne CO_2 TJ^{-1} or similar):

(i) Current year (annual): For example, LCA for year 2030 is based on annual CO_2 emissions per unit of annual bioenergy production in 2030, LCA for year 2035 on annuals for 2035, etc. This is the most straightforward option, but results may be highly variable over time, and sensitive to one-time land use change events and thus exhibit excessively large emissions for early years of bioenergy deployment.

(ii) Fixed average based on cumulative effects for a chosen time: For example, LCAs for any year between 2025 and 2070 are based on cumulative CO_2 emissions in 2025–2070 divided by the total amount of bioenergy produced in the same time interval. This option distributes effects evenly over the chosen period. It is thus insensitive to large one-time emission fluxes and avoids uncertain allocation of emissions to specific years, but it can have the artifact that bioenergy production is assigned responsibility for emissions that happened decades before. Another artifact can be that a different chosen time horizon leads to different cumulative effects.

(iii) Running cumulative from a chosen start year: For example, with 2025 as start year, LCA for year 2030 is based on cumulative CO_2 emissions for 2025–2030 per unit of cumulative bioenergy production, LCA for 2035 on cumulative values for 2025–2035, etc. This option can make results less sensitive to one-time events compared to option (i) above. A different chosen time horizon can lead to different cumulative effects similarly as with option (ii). Results for the end year of the time horizon will be the same for option (ii) and (iii), but results for intermediate years can be different.

2.5. Life cycle assessment

We here describe the LCA datasets used for the case study of global grassy bioenergy crops. We distinguish between a default LCA dataset that is independent of MAgPIE modelling and scenarios (the 'Default dataset'), and scenario-based variants that incorporate MAgPIE scenario results (the 'scenario-based dataset'). In general, connections to the LCA database Ecoinvent (Wernet *et al* 2016, Ecoinvent 2019) are made to cover supply chains of fertilizers, pesticides, machinery and other inputs. The software that accompanies this paper loads the default dataset and creates scenario-based dataset variants by replacing default coefficients with coefficients derived from the scenarios.

Table 1. Overview of assumptions and sources for default LCA dataset. Asterisk indicates stressors that are included in the software and data accompanying this article (see Data availability statement), but that do not contribute to impact categories selected for final analysis and presentation of results (i.e., land occupation and greenhouse gas emissions).

	Default LCA dataset
Land occupation	Assume default yield value 20 t DM ha^{-1} yr^{-1} and gross energy content 18 GJ t^{-1}. This yields land occupation of 27.8 km^2 yr^{-1} PJ^{-1}.
Nitrogen fertilizer (as N)	Assume 4.8 t t^{-1} biomass based on Wang *et al* (2012), Ashworth *et al* (2015), Ecoinvent (2019) (miscanthus), and Escobar *et al* (2017). Include 2 t packaging per t fertilizer as N (Ecoinvent 2019).
Phosphorus fertilizer (as P2O5)	Assume 4.8 t t^{-1} biomass. Include 2 t packaging per t fertilizer as P2O5. Sources are the same as for nitrogen fertilizer.
Pesticides	Assume 0.15 kg t^{-1} biomass based on Ashworth *et al* (2015), Ecoinvent (2019) (miscanthus), Escobar *et al* (2017) and Morales *et al* (2015). Include 2 t packaging per t pesticide (Ecoinvent 2019).
Seed	Assume 1% of production is used as seed (consistent with MAgPIE).
Irrigation	Assume 250 m^3 t^{-1} biomass based on Escobar *et al* (2017), assuming site with relatively low irrigation is most representative.
Diesel use by agricultural machinery	Assume 150 MJ t^{-1} biomass based on Wang *et al* (2012), Ashworth *et al* (2015) and Escobar *et al* (2017). Assume lubricating oil corresponding to 4.5% of diesel fuel based on Athanassiadis *et al* (1999), Dias and Arroja (2012), and Morales *et al* (2015).
Transport of biomass	Assume 100 km lorry transport (Field *et al* 2020)
CO_2 and CH_4 to air	CO_2 and CH_4: Omitted, outside of scope of default dataset.
N_2O and NH_4* to air	Assume 1% N_2O-N and 2% NH_4-N per N fertilizer based on IPCC (2006) and Nemecek and Kägi (2007).
NO_x to air*	Assume 21% NO_x emission per N_2O emission (Nemecek and Kägi 2007).
NO_3- to ground water*	Assume 10% NO_3-N per per N fertilizer, based on lower-bound values in (IPCC 2006).
Phosphorus (particulates) to surface water*	Assume 1.27 kg P per kg biomass (Ecoinvent 2019) (miscanthus).
PO_4^{3-} to surface water*	Calculate 28 μg PO_4^{3-} per kg biomass based on Nemecek and Kägi (2007).
Pesticides to soil*	Assume amount emitted to soil equals amount applied.
Natural land transformation*	Omitted, outside of scope of default dataset.

Table 1 displays assumptions and sources for the default LCA dataset. This dataset contains only fixed (scenario-independent) coefficients and is established based on different sources and assumptions. It is the LCA dataset before the integration of MAgPIE scenarios.

Table 2 presents the assumptions, sources and approaches to generate the scenario-based LCA datasets, using the default LCA dataset presented above as a starting point. We generate 18 individual datasets for each modeled year in correspondence with the 18 scenarios (section 2.3).

As table 2 indicates, the differences in aggregate variables approach (section 2.1) is employed for land occupation, nitrogen and irrigation requirements, and CO_2, CH_4, N_2O and NH_4 emissions. The differences in aggregate variables approach is our preferred option because it captures total ('direct' and 'indirect') effects on the agricultural sector, and can be applied consistently for all variables defined in MAgPIE outputs. Further, we use the fixed average approach for quantifying land use-related CO_2 to capture long-term developments while avoiding uncertain allocation to specific years (section 2.4).

To aggregate CO_2, CH_4, N_2O into total anthropogenic GHG emissions, we use IPCC AR5 100-year global warming potential (GWP) conversion factors of 28 and 265 for CH_4 and N_2O, respectively. The 100-year GWP has traditionally been the default metric used by The United Nations Framework Convention on Climate Change (UNFCCC). Other metrics, such as the 20-year GWP or the 100-year global temperature potential, differ in concept or account for the time-based characteristics of gases differently (Shine *et al* 2005). Results are usually sensitive to the use of alternative metrics when emissions of short-lived species (e.g., CH_4) are prominent, while they tend to provide similar results when emissions of CO_2 and other long-lived gases are dominant. In our cases, emissions of CH_4 are relatively small, so we do not expect variations in our main findings if other metrics than GWP100 are used to characterize the impacts.

3. Results

We divide this section into two parts, which presents results obtained solely from MagPIE land use modelling (section 3.1) and results after scenario integration into LCA (section 3.2).

Table 2. Overview of assumptions and sources for scenario-based LCA datasets. Asterisk indicates stressors that are included in the software and data accompanying this article (see Data availability statement), but that do not contribute to impact categories selected (i.e., land occupation and greenhouse gas emissions) for final analysis and presentation of results.

	Scenario-based LCA datasets
Land occupation	Calculated from MAgPIE scenario outputs using differences in aggregate variables approach (section 2.1).
Nitrogen fertilizer	Same as above.
Phosphorus fertilizer	Same as default LCA dataset owing to lack of scenario-specific information.
Pesticides	Same as above.
Seed	Same as above.
Irrigation	Calculated from MAgPIE scenario outputs using differences in aggregate variables approach (section 2.1).
Diesel use by agricultural machinery	We use the default diesel consumption, $diesel_{def}$, of 150 MJ t^{-1} and land occupation, $land_{def}$, of 28 km^2 yr^{-1} PJ^{-1} from table 1 as a starting point. We then assume diesel per unit biomass changes in proportion to the relative change in land occupation, scaled by 0.5, following the formula: $\mathrm{diesel}_{sce} = \mathrm{diesel}_{def} + 0.5 \times \mathrm{diesel}_{def} \times (\mathrm{land}_{sce} - \mathrm{land}_{def})/\mathrm{land}_{def}$ $diesel_{sce}$ is the scenario-specific diesel consumption and $land_{sce}$ the scenario-specific land occupation. We assume this linear adjustment can be applied for the range of land occupation values observed in our land use model results (i.e., rage 12–28 km^2 yr^{-1} PJ^{-1}, as depicted later in figure 3). For example, if $land_{sce}$ is 14 km^2 yr^{-1} PJ^{-1}, $diesel_{sce}$ is 113 MJ t^{-1}. Finally, we assume lubricating oil corresponding to 4.5% of diesel fuel (based on references in table 1).
Transport of biomass	Same as default LCA dataset.
CO_2 and CH_4 to air	Calculated from MAgPIE scenario outputs using differences in aggregate variables approach (section 2.1) and for CO_2 the fixed average approach (section 2.4).
N_2O and NH_4* to air	Calculated from MAgPIE scenario outputs using differences in aggregate variables approach (section 2.1).
NO_x to air*	Assume 21% NO_x emission per N_2O emission (Nemecek and Kägi 2007). Hence, NO_x scale in proportion to N_2O as calculated from MAgPIE outputs.
NO_3- to ground water*	Assume 10% NO_3-N per per N fertilizer, based on lower-bound values in IPCC (2006). Hence, NO_{3-} scale in proportion to nitrogen fertilizer use as calculated from MAgPIE outputs.
Phosphorus (particulates) to surface water*	Same as default LCA dataset.
PO_4^{3-} to surface water*	Same as default LCA dataset.
Pesticides to soil*	Same as default LCA dataset.
Natural land transformation*	Calculated from MAgPIE scenario outputs using differences in aggregate variables approach and fixed average approach as for CO_2.

3.1. Land use model results

While our study presents a global assessment, the underlying analysis with MAgPIE is multi-regional. As explained previously in section 2.2, the calculations are based on 18 scenarios, comprising two bioenergy demands (B50 and B100), three SSPs (SSP1, SSP2, SSP5) and three CO_2 tax levels (T0, T40, T200). As background to understand global results presented later, figure 1 illustrates how MAgPIE chooses to allocate grassy bioenergy production to main world regions over time. The MAgPIE scenarios that will be used for integration into LCA allow irrigation and are represented by figure 1(a) and (b). Alternative scenario runs without irrigation for bioenergy production are shown in figure 1(c); these are included here for context and illustrative purposes but are not part of the scenario integration into LCA in our study. In B50 and B100 alike, the bulk of production occurs in Latin America (LAM), India (IND), United States of America (USA) and China (CHA), in that order of importance. In addition, Sub-Saharan Africa (SSA) contributes modestly after 2055 in B100. There are small-to-moderate contributions from other regions (aggregated to 'Other' in figure 1).

In our scenarios, irrigation is the primary factor enabling bioenergy production in India. Without irrigation, bioenergy production is minimal due to the country's largely unfavourable conditions for rainfed agriculture (figure 1(c)). The scenarios assume future investments in irrigation infrastructure to enhance productivity on marginal lands, thereby making bioenergy production viable. While this assumption may seem optimistic given India's current constrained hydrological budgets (Devineni *et al* 2022), the scenarios are deliberately exploratory, focusing on potential supply, rather than goal-oriented. This approach allows for a wide range of possible future outcomes in the LCA analysis and helps to identify areas where system transformations can achieve the largest benefits. For Sub-Saharan Africa after 2055 in B100 (figure 1(b)), yield-increasing technological change leads to food production with declining land intensity. This releases agricultural land, which progressively becomes abandoned, allowing for gradual bioenergy expansion at reduced competition for land and water between food and energy crop production.

Figure 2 compares world-average land use-related CO_2 emission factors for grassy energy crops over time with the three calculation options (section 2.4): fixed average, running cumulative and current year. The results represent combined land use and land use change CO_2, and overall range approximately from 2 to 35 tonne CO_2 TJ^{-1} across the different scenarios and accounting options. The running cumulative (figures 2(b), (e), (h)) and

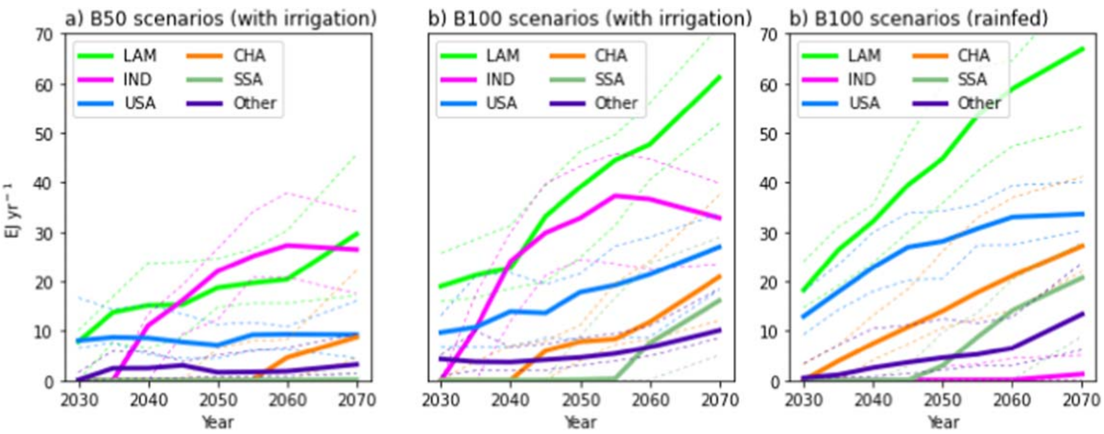

Figure 1. Grassy bioenergy production for main world regions for B50 (a) and B100 (b) scenarios respectively. For each panel (B50 and B100), results are based on nine MAgPIE scenarios with combinations of three SSPs and three GHG price trajectories. Thick solid lines represent medians and dotted lines maximum and minimum across nine B50 and B100 scenarios, respectively. LAM Latin America; IND: India; USA: United States of America; CHA: China; SSA: Sub-Saharan Africa. 'Other' is an aggregate of seven other regions.

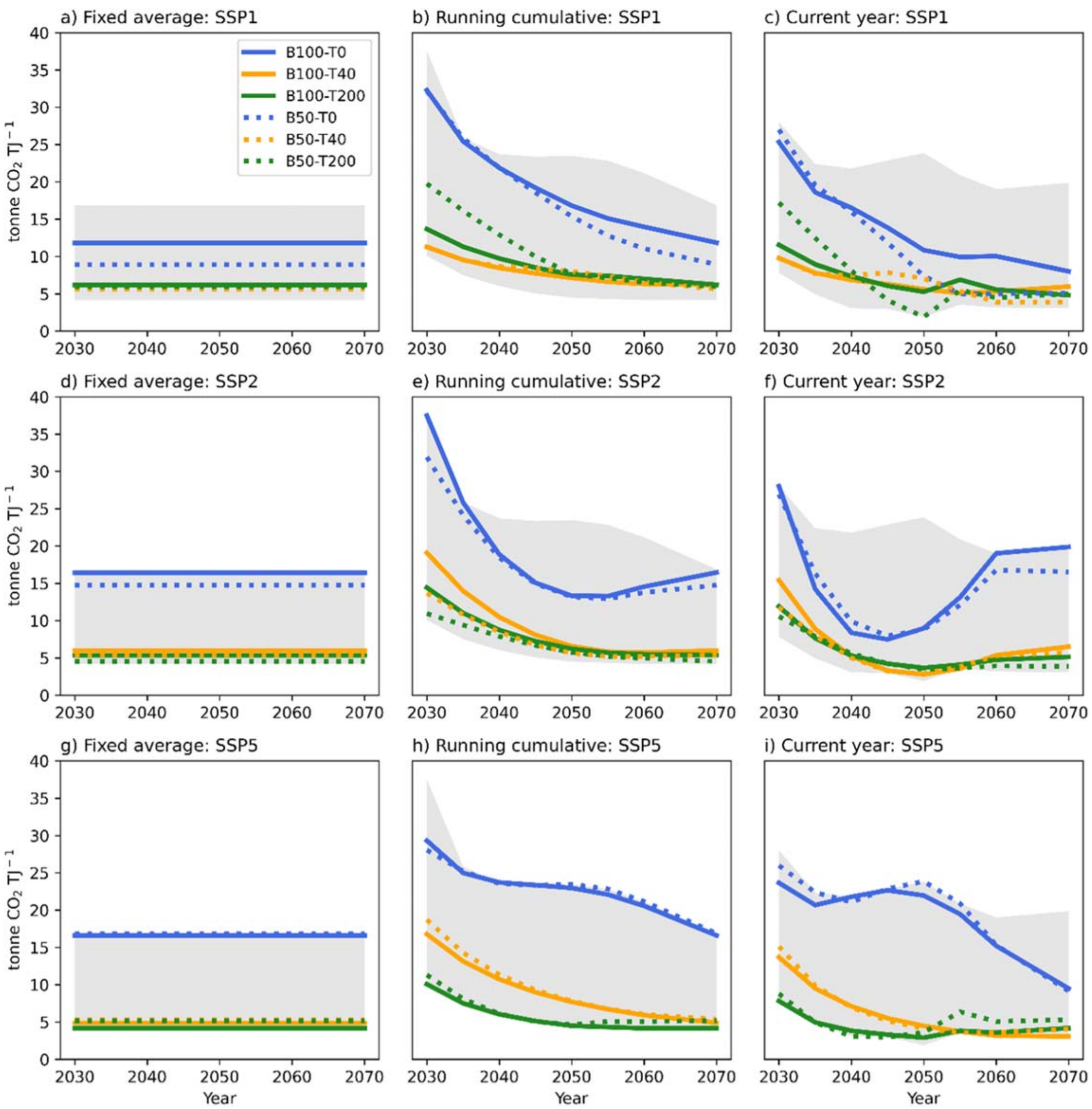

Figure 2. Coefficients for land use-related CO_2 emissions per unit of bioenergy using the approaches of (a) fixed average, (b) running cumulative and (c) current year (annual). Thick solid or dashed lines represent selected individual scenarios (six scenarios in each subplot) and shaded areas the total ranges across eighteen scenarios.

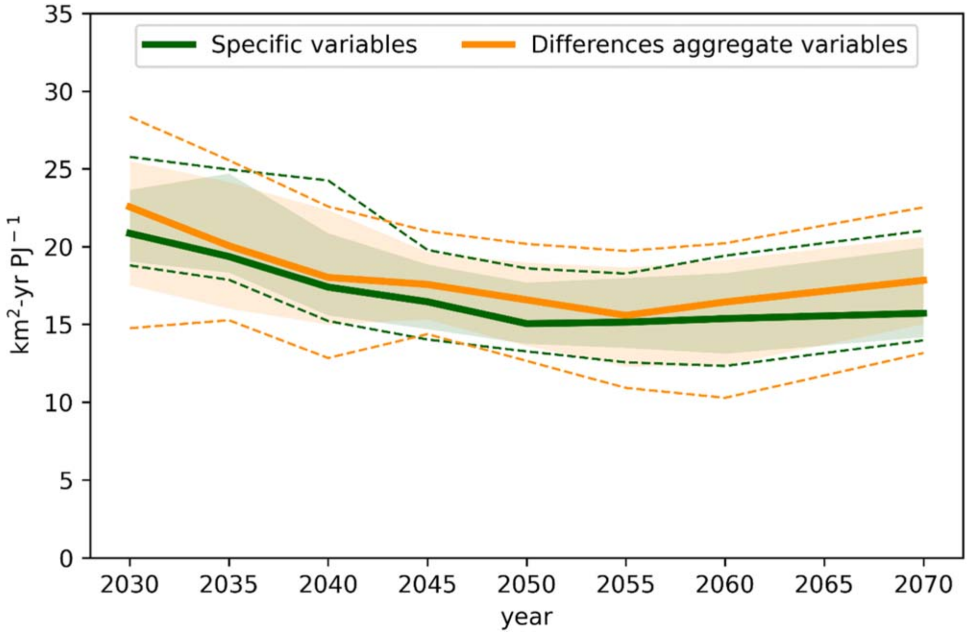

Figure 3. Coefficients for agricultural land occupation for grassy energy crops using the approaches of specific yield variables and differences in aggregate variables. Thick solid lines represent medians and shaded areas 10%–90% ranges across eighteen MAgPIE scenarios. Upper and lower dotted lines represent maximum and minimum, respectively, across eighteen scenarios.

current year (figures 2(c), (f), (i)) approaches yield relatively large CO_2 emissions for early years of bioenergy deployment. This is attributable to relatively small production volumes and sensitivity to individual land use change from land clearing and crop establishment causing large emission fluxes in early years. The coefficients generally, but not always, decline over time with these two approaches. The fixed average approach (figures 2(a), (d), (g)) exhibits the lowest coefficients in early years (especially before 2040) but may exhibit h.c. than the other approaches for late years. This is because with this approach, all coefficients are determined based on cumulative values until 2070, and thus coefficients for early years 'benefit' from high production in late years.

It follows from the definition of the fixed average approach that coefficients are constant over time. In contrast, the running cumulative and current year approaches show declining trends overall and, especially for T40 and T200, tend to plateau in late years towards 2070.

Figure 2 also shows that the emissions are considerably higher without CO_2 taxation (T0). The effect of taxation has a stronger effect on CO_2 emissions than the bioenergy demand itself. Across all scenarios, B100-T200 has a similar profile to B50-T200, and overall smaller emissions than B50-T0. Emissions per unit bioenergy do not scale linearly with the demand of bioenergy, but depend on the policy context. This indicates the importance that governance can play for reducing the climate impacts connected to bioenergy deployment, as a regulated international land use framework can reduce risks associated with direct and indirect deforestation and prioritize bioenergy crops on marginal or abandoned cropland. At the same time the difference in emissions between moderate (T40) and high (T200) CO_2 taxation are rather small, suggesting that already moderate taxation can suffice to prevent major emissions. The difference between T0 and T40/T200 is smallest for SSP1 with a factor of around two, while the factor is around 3 for SSP2 and SSP5. This reflects lower population growth and lower competition for land due to more sustainable diets (less livestock) in SSP1.

The differing dynamics in B100-T0 across SSP1, SSP2 and SSP5 in figure 2 are caused by multiple overlapping and partly counteracting factors. These factors include stricter water protection policies that reduce irrigation, leading to more land conversion in SSP1/SSP5 (this contributes to higher emissions in SSP1/SSP5); and lower population growth and agricultural demand in SSP1/SSP5 compared to SSP2 (contributing to lower emissions in SSP1/SSP5). After around 2050, CO_2 emissions from LUC decrease in SSP1/SSP5 as population growth stabilizes, while in SSP2, emissions increase due to delayed population peaking and rising bioenergy demand.

Figure 3 compares coefficients for land occupation based on crop-specific variables and differences in aggregate variables. The value 20 km^2-yr PJ^{-1}, roughly a middle range value in the figure, is equivalent to 28 t DM ha^{-1} yr^{-1} if assuming 18 GJ t^{-1}. The land use values depicted in figure 3 are broadly similar for the two approaches with the median of the aggregate variables being constantly slightly higher than the one of the specific variables. Land use decreases from 2030 to around 2050 but not so after around 2050. This has to do with effects of yield-increasing technological progress dominating before 2050, and effects of increasing scarcity of

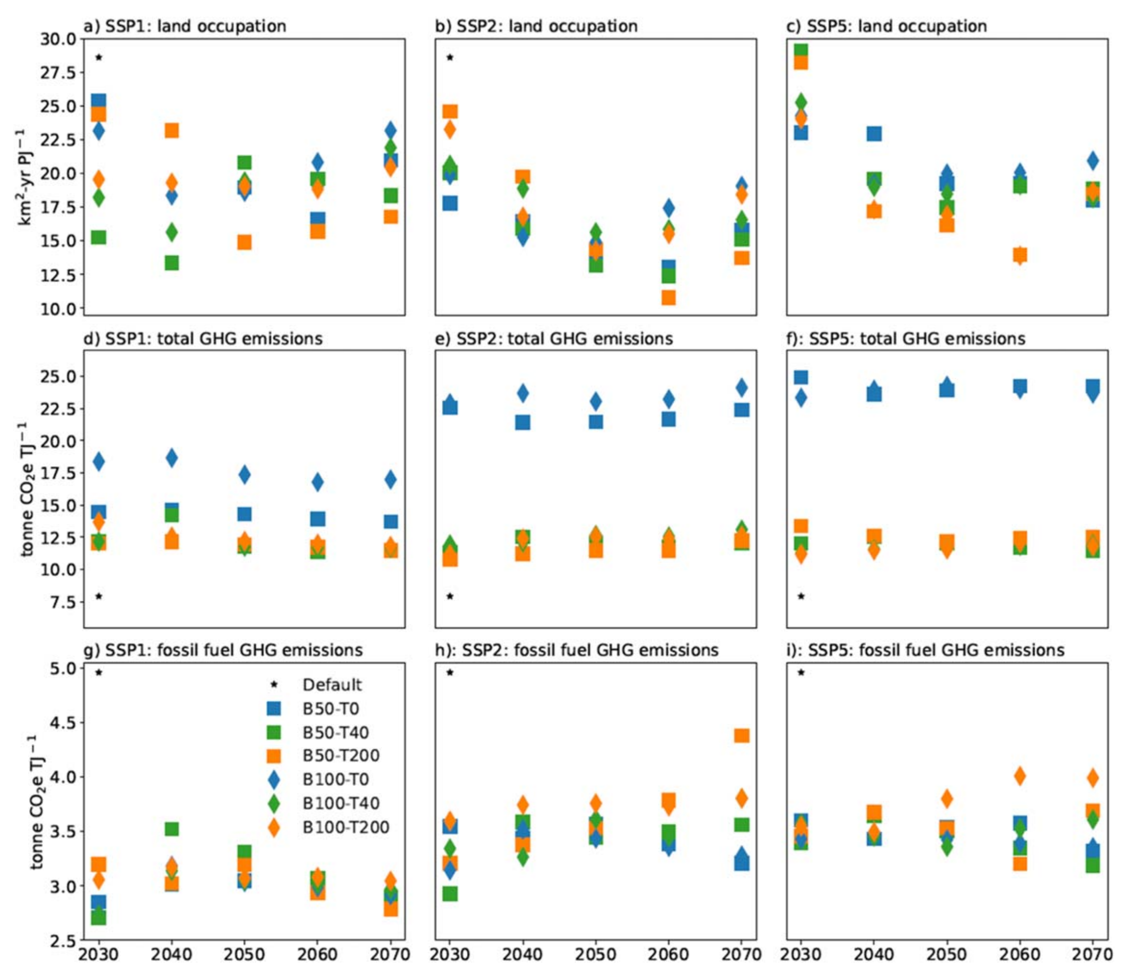

Figure 4. Life cycle land occupation (a)–(c), total anthropogenic GHG emissions (d)–(f), and fossil fuel GHG emissions (g)–(i) for grassy energy crops in 2030–2070 for a total of eighteen scenarios (six unique scenarios in each row of subplots).

productive land dominating after 2050. Somewhat broader ranges are evident for the differences in aggregate variables approach, which could be interpreted as reflecting greater uncertainty for this approach.

Given that the B50 and B100 demands are defined at the global level, results from the differences in aggregate variables approach are only meaningful at global scale[9]. Results derived from crop-specific variables from MAgPIE are provided in figure A1 in the appendix, however. Among the major producing regions of bioenergy (see figure 1), India stands out with low specific land use per bioenergy production (figure A1). Land scarcity in India in combination with growing food demand drive investments in yield-increasing technological change. Due to spill-over effects, technological change does not only benefit food and feed crops yields but also increases bioenergy crop yields.

3.2. Life cycle assessment results

While the results presented previously in section 3.1 are solely based on the MagPIE model, results in the current section include LCA calculations with scenario integration. Figure 4 presents an overview of results from LCAs with scenario integration (based on the 18 scenarios from section 3.2), as well as for the default LCA case (i.e., without scenario integration), which is included for comparison. Results for land occupation displayed in figures 4(a)–(c) are distinguished from results related to land use in section 3.1 in that they cover both urban and agricultural land use and include land use occurring upstream in supply chains (e.g., land use associated with fertilizer and other materials production). Contributions from supply chain land use are consistently small (a few percent) across scenarios, however.

Land occupation per unit bioenergy is overall comparable for the different demand scenarios. The median of B100 sample values for 2030–2040 is 19.2 km^2-year PJ^{-1} and for B50 22.1 km^2-year PJ^{-1}. The median of B100 values for 2060–2070 are 18.8 km^2-year PJ^{-1} and for B50 16.6 km^2-year PJ^{-1}. Differences in land occupation can

[9] If we were to obtain the same type of results for different regions, we would need to re-run MAgPIE with regional bioenergy demand scenarios replacing the global B0, B50 and B100 scenarios.

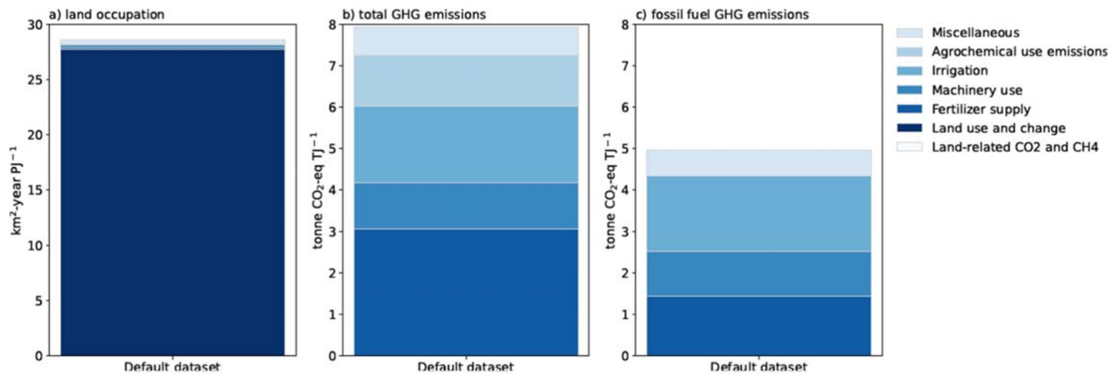

Figure 5. Breakdowns of life cycle land occupation (a), total anthropogenic GHG emissions (b) and fossil CO_2 and CH_4 only GHG emissions (c) for grassy energy crops using default (i.e., scenario-independent) LCI dataset. In both figures 5 and 6, 'Land-related CO_2 and CH_4' refers to emissions as quantified by MAgPIE. 'Land use and change' represents agricultural land use; 'Fertilizer supply' represents fertilizer supply chains; 'Machinery use' includes fuel oil and machinery supply chains as well as direct emissions from fuel burning; 'Irrigation' represents effects water supply; and 'Agrochemical use emissions' N_2O emissions from agriculture.

be mainly explained by deviations in investments into land saving R&D. In particular, high demand can trigger more R&D investments and thereby leading to lower land occupation per unit bioenergy. However, R&D investments in the scenario are mainly determined by the choice of the SSP scenario as well the biophysical condition and less so by the different bioenergy demands, leading to a rather inconclusive picture when looking at land occupation rates in single scenarios.

There is a tendency for high GHG price to yield lower land occupation, with the median of all T200, T40 and T0 2030–2070 values being 18.0, 18.3 and 19.1 km^2-year PJ^{-1}, respectively.[10] These results suggest a co-benefit of GHG price in terms of reduced land use, although the effect is not especially strong in general. The co-benefit can be explained by less (emission intensive) land expansion and more land use intensification via investments into technological change with GHG taxation. Land occupation is generally higher for SSP1 and SSP5 than SSP2. This is primarily attributable to stricter water protection policies in SSP1 and SSP5 (environmental flow protection) which restrict the water available for irrigation. Reduced water availability for irrigation translates into more conversion of forest and other natural land to cropland in SSP1/SSP5, which results in higher land occupation in SSP1/SSP5 compared to SSP2.

Figures 4(d)–(f) shows the total anthropogenic GHG emissions including the contributions from impacts of both land use emissions and the fossil fuel emissions from the supply chain, while figures 4(g)–(i) shows supply chain impacts only. Land use-related CO_2 is the main contributor to total GHG impacts, but, as will be addressed later in this section, there are also non-negligible contributions from fossil fuel emissions. For total anthropogenic GHG emissions (figures 4(d)–(f)), for which CO_2 emissions is a dominant contributor, the presence or absence of a GHG price is the key factor, consistent with what observed in figure 2. For scenarios with GHG taxation, larger (B100) or lower (B50) bioenergy demand does not consistently correlate with emissions, as all the values are at a similar level. The main difference is thus connected to whether there is a GHG tax or not, rather than the amount of bioenergy supplied. Lower differences occur in SSP1, as this is the most sustainable pathway where improvements in the agri-food sector, dietary changes, land use regulations, and relatively low population growth contribute to decreased competition for land and thus reduce risks of deforestation.

Fossil CO_2 and CH_4 emissions are quite mixed across different bioenergy demands, shared socioeconomic pathways and GHG price (figures 4(g), (h), (i)). There is a tendency for SSP1 to show lower emissions than SSP2 and SSP5. This is mainly attributable to lower fertilizer and irrigation requirements, which is again related to SSP1 being the most sustainable pathway, including improvements in the agricultural sector. For SSP2 and SSP5, some high fossil emissions can be observed for scenarios with high GHG price (T200), suggesting a trade-off between agricultural and fossil CO_2, but the evidence is not clear. Emissions for the default dataset (indicated with an asterisk in the figure), which is independent of MAgPIE scenarios, are higher than for the scenarios based on MAgPIE, in large part owing to higher demands for irrigation. In general, stronger reductions in supply chain fossil fuel emissions over time can be expected if changes towards LCA background system were considered.

Figures 5 and 6 show LCA results broken down into main categories of contributing activitites. Results for the default LCA dataset indicate total land occupation of 29 km^2-year PJ^{-1}, of which 97% is agricultural area

[10] This is based on the differences in aggregate variables approach. With specific variables we see the same behavior with overall lower land occupancy in taxation scenarios, but with overall lower values given that the indirect effects are unaccounted (T200=17.8, T40=17.7 and T0=18.5 km^2/year/PJ).

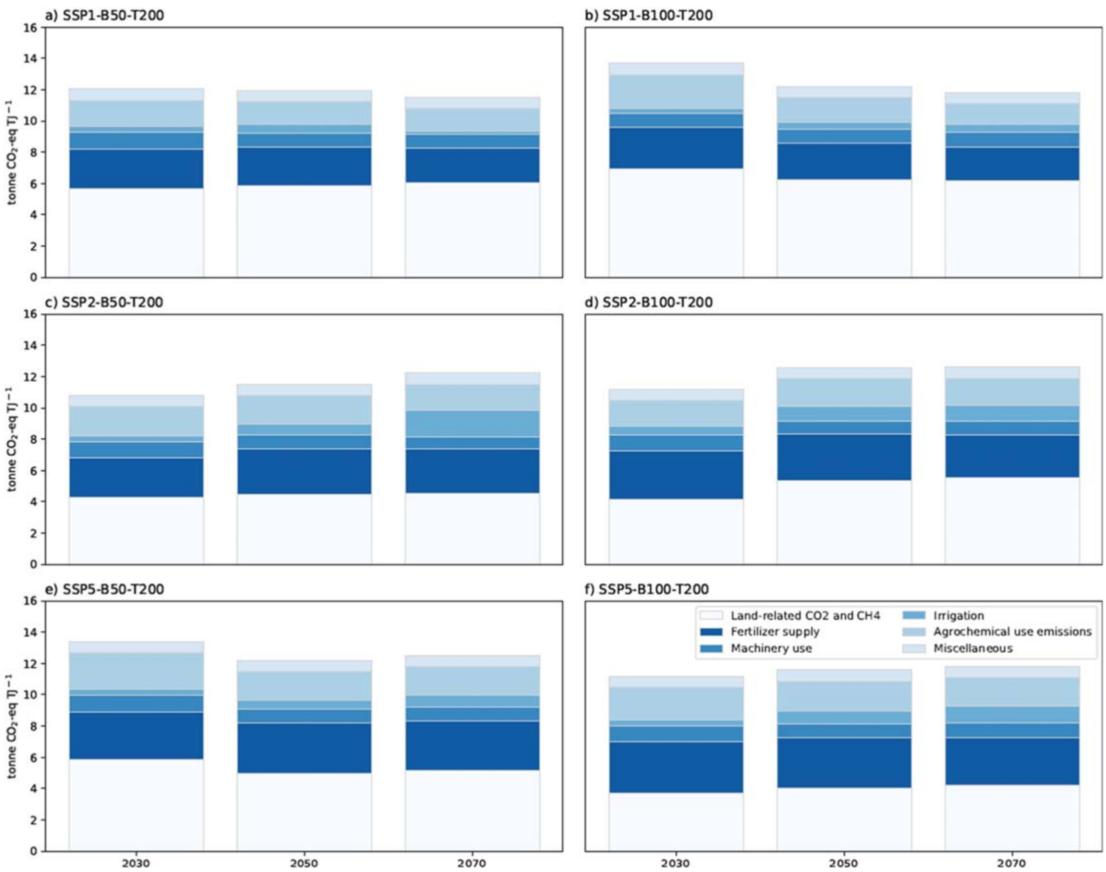

Figure 6. Breakdowns of total GHG emissions for grassy energy crops for six scenarios (a)–(f) in 2030–2070. T200 scenarios are shown as an example with high governance of land use-related CO_2 emissions. For definitions of stacked categories, see figure 5 caption.

occupied by the energy crops themselves and the remainder is attributable to seeds application and agricultural and urban land occupation upstream in supply chains (figure 5(a)). Similarly, impacts from total GHG emissions amount to 7.9 t CO_2e TJ^{-1} (figure 5(b)) and 5.0 t CO_2e TJ^{-1} if counting fossil CO_2 and CH_4 only (figure 5(c)). Notable sources of non-fossil emissions are N_2O from crops ('Agrochemical use emissions' the figures) and N_2O from production of nitric acid, an input to nitrogen fertilizer production (subsumed under category 'Fertilizer supply'). Fertilizer supply is the strongest contributing activity to emissions, followed by irrigation, whose emissions are predominantly due to water pumps mostly driven by electricity (and some by diesel).

Even for the scenarios with high GHG price (T200), agricultural CO_2 is the major source of total GHG emissions. Other sources combined contribute the same order of magnitude as agricultural CO_2 to total emissions. Despite fixed values for CO_2 across years due to the fixed average approach, 'Land-related CO_2 and CH_4' vary across years in figure 6 due to varying CH_4. Some negative CH_4 emissions values occur (22% of CO_2 emissions at the most and 12% at the second most). Emissions associated with both fertilizers, irrigation and machinery (which correlate inversely with yields) are rather constant over time (figure 6).

4. Discussion

Our analysis involves some mixing of average data and data relating to a change, which is sometimes argued as undesirable (Heijungs 1997, Ekvall *et al* 2005). This mixing occurs because average data, including for background processes, are combined with data resulting from an assumed change in bioenergy demand. Also, the differences in aggregate variables approach implies that certain activities (e.g., food production) not linked to bioenergy through actual flows of materials, energy or services contribute to the LCA of bioenergy, which may be seen as inconsistent with attributional LCA (Sandén and Karlström 2007, Majeau-Bettez *et al* 2018). At the same time, our approach allows for implicitly dealing with the fundamental underlying issues of land as a limited global resource, competition over global land, and land systems as co-producers of biomass for different purposes (Fujimori *et al* 2019). Furthermore, when the goal is to analyse future scenarios for deployment starting from low levels and rising to high levels, clear distinctions between average and change effects can be intrinsically difficult to establish.

Previous estimates of land use-related CO_2 emissions vary widely depending on feedstocks, methodology and region (Creutzig *et al* 2015, Jeswani *et al* 2020). Our results (fixed average approach) appear well below the upper range of estimates in literature (Ahlgren and Di Lucia 2014, Daioglou *et al* 2020), but appear consistent with results from scenarios in the IAM-based EMF-33 project (Rose *et al* 2020). Our T40 and T200 results appear in the lower range of estimates in literature (Ahlgren and Di Lucia 2014, Daioglou *et al* 2020).

The scenarios with indirect protection of forests through CO_2 taxes (T40 and T200) exhibit emissions around a half or a third of the emissions with zero tax (T0), but little differences occur between T40 and T200. This indicates that governance of emissions from land use change, via CO_2 taxes in our modelling, is highly important up to a certain level but less so when moving from moderate to high governance taxation. Further, in T40 and T200, GHG emissions per unit bioenergy remain similar in B50 and in B100 (which has twice the demand of B50), suggesting that GHG emissions per unit of bioenergy do not increase with bioenergy demand in presence of an emission tax in the analyzed demand range.

The assumption in T40 and T200 that CO_2 emissions from all forms of land-use change are uniformly priced reflects an idealized policy scenario. Although a clear implementation pathway for achieving such policy coherence is not yet established in policy discussions, comprehensive CO_2 emission pricing in the land system is a critical mechanism for the international community to protect carbon-rich ecosystems (Popp *et al* 2014).

One limitation of the analysis is that effects on soil organic carbon within cropland are excluded because MAgPIE's treatment of soil carbon density currently does not distinguish different types of cropland. However, perennial grasses can sequester soil carbon at potentially high rates owing to their deep root systems (Valin *et al* 2015, Jeswani *et al* 2020). Estimates in the literature vary substantially but generally indicate that perennial grasses cultivated on former croplands could yield soil carbon sequestration of 0.2–2.2 t C $ha-^{1}$ yr^{-1} on average over a few decades (Don *et al* 2012, Qin *et al* 2012, Qin *et al* 2016, McCalmont *et al* 2017). This is equivalent to 2.0–20 t CO_2 TJ^{-1} for an average yield of 20 t DM ha^{-1} yr^{-1} at 18 GJ t^{-1}, which is somewhat lower but same order of magnitude as our results. On the other hand, there may be no soil carbon sequestration benefits if perennial grasses are cultivated on former grasslands or forests (Don *et al* 2012, Qin *et al* 2016).

Overall, this study proposes an approach and make available data and software for integrating global land use model scenarios into LCA, facilitating systematic scenario integration of not just total land use change CO_2 emissions, but also of total effects on CH_4 and N_2O emissions and land, fertilizer and irrigation requirements within a consistent framework. Owing to the use of a land use model with global coverage, uncertain and artificially constructed distinctions between 'direct' and 'indirect' emissions are avoided, as all emissions become 'total'. The approach favors consideration of direct and indirect effects associated with irrigation, machinery fuel and fertilizer use as well as emissions. Thanks to a global spatial coverage and temporal dimension, it facilitates a systematic and consistent inclusion of indirect effects in a global analysis framework.

The approach, data and software can be built on in future research. They are suitable for application within the framework of climate protection scenarios of the IPCC–for example through adopting the SSPs as in the present study–climate protection targets or climate change impact scenarios, or through integrating future scenario changes into the LCA background system. The latter can be pursued by building on existing efforts (Mendoza Beltran *et al* 2020, Sacchi *et al* 2022) and identified GHG mitigation strategies for agricultural bioenergy (Kwon *et al* 2021), and aligns with the idea that foreground and background systems should be consistently defined in prospective LCA (Arvesen and Hertwich 2011, Gibon *et al* 2015, Arvidsson *et al* 2018). As an illustrative example, we may consider GHG emissions associated with machinery fossil diesel use[11]. These emissions amount to 0.8 t CO_2e per TJ biomass in scenario SSP2-B50-T200 for the year 2050. Replacing fossil diesel by biodiesel produced from biomass from scenario SSP2-B50-T100 could reduce the emissions by three-fourths (from 0.8 to 0.2 t CO_2e per TJ)[12]. Using cleaner energy throughout the supply chain (including in transport) of various commodities will further reduce emissions.

Future work may test the approach for specific world regions, other bioenergy feedstocks or impact categories, or for scenarios with even higher bioenergy deployment than in the present work. Using the approach for other regions or feedstocks will require new land use model runs with bioenergy demand set for the specific region and feedstock in question. We will welcome further discussion on the suitability of the approach and methods choices.

[11] Reflected as 'Machinery use' in figure 6, with the small difference that 'Machinery use' in figure 6 also includes minor emissions from machinery and lubricant production.

[12] Calculated with results for SSP2-B50-T200 and year 2050 from the current analysis, combined with assumed additional GHG emissions of 8.3 kg CO_2e t^{-1} from industrial conversion and 3.2 kg CO_2e t^{-1} from transport from biorefinery, and a 45% Fischer–Tropsch conversion efficiency (Gvein *et al* 2023).

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Conflict of interest statement

The authors declare no conflict of interest.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://git.list.lu/best/best-foreground.

Appendix. Regional land occupation factors

Figure A1 shows land occupation for grassy energy crops using specific yield variables for the five most important regions in terms of grassy bioenergy production (see figure 1) and aggregate global results ('World'). The global results are an aggregate of twelve world regions in total.

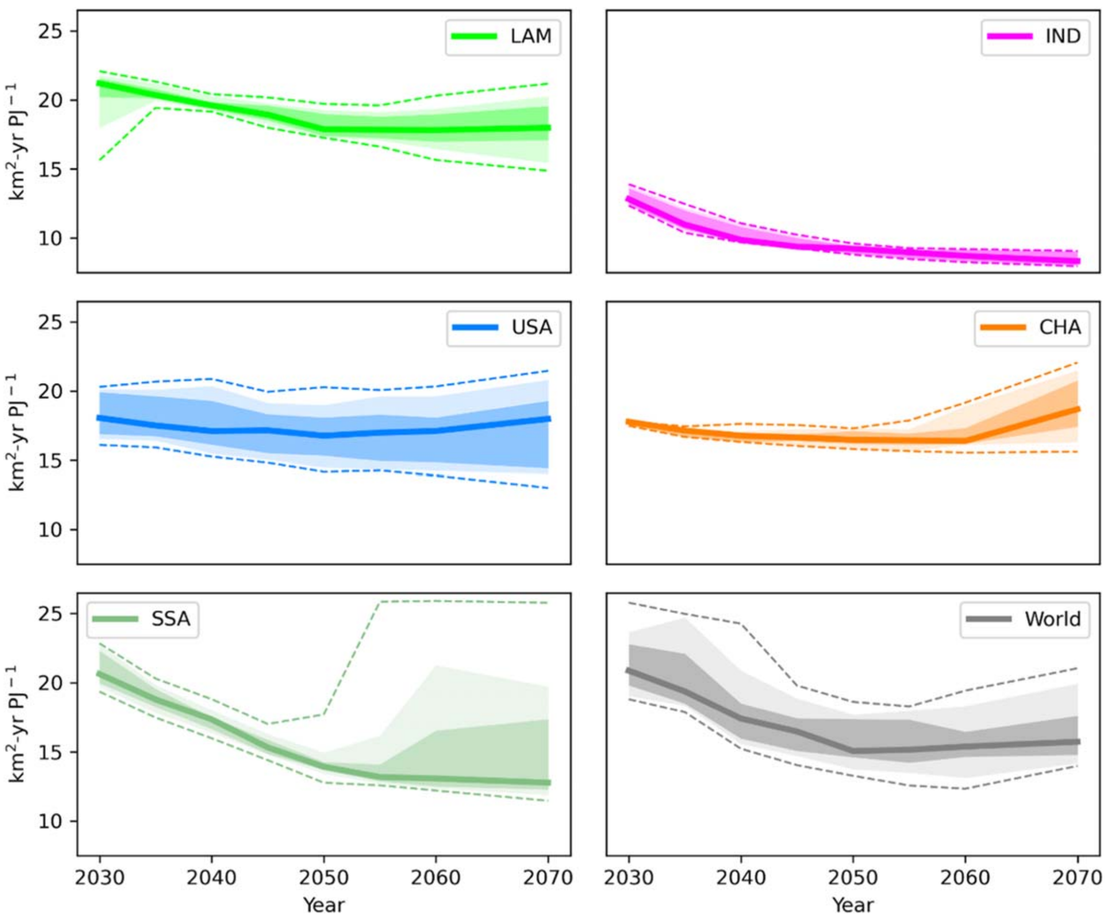

Figure A1. Agricultural land occupation for grassy energy crops based on specific yield variables calculated by MAgPIE. Thick solid lines represent medians, light shaded areas 10%–90% percentiles and dark shaded areas 25%–75% percentiles across eighteen scenarios. Upper and lower dotted lines represent maximum and minimum, respectively, across eighteen scenarios. Results are based on 18 MAgPIE scenarios. LAM Latin America; IND: India; USA: United States of America; CHA: China; SSA: Sub-Saharan Africa. 'World' is aggregate of twelve world regions in total.

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