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Metrics on the sustainability of region-specific bioplastics production, considering global land use change effects

Neus Escobar [a,b,c,*], Wolfgang Britz [b]

[a] Biodiversity and Natural Resources Program, International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, 2361 Laxenburg, Austria
[b] Institute for Food and Resource Economics (ILR), University of Bonn, Nussalle 19, 53115 Bonn, Germany
[c] Center for Development Research (ZEF), University of Bonn, Genscherallee 3, 53113 Bonn, Germany

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ABSTRACT

Expanding the production of fuels and fibres based on traditional food crops can put additional pressures on ecosystems and natural resources, with potential spillover effects through induced land use change (iLUC). Computable General Equilibrium (CGE) modelling provides a systematic framework for ex-ante sustainability analysis, capturing the complex interactions between land uses, agri-food markets, and international trade. This study applies an integrated CGE framework that considers loss of natural vegetation to derive quantitative indicators on the sustainability of manufacturing bioplastics from arable crops in five major producing regions (Brazil, China, the European Union, United States and Thailand). The approach consists of increasing bioplastics production at the cost of conventional plastics in each of these regions separately by means of a production subsidy, simulating bioplastic production targets. In order to assess the uncertainty in sustainability metrics, different levels of market penetration are considered, as well as variability in key model parameters. Increasing bioplastics production in Thailand is in general associated with more favourable metrics, although this is related to the relatively small size of the sector, which triggers minor market-mediated effects. When iLUC is included, increased bioplastics production in China is, on average, associated with the largest land footprint (16.93 ha t^{-1}); whereas the highest CO_2 emission intensity is estimated for bioplastics produced in the European Union (10.41 t CO_2-eq. t^{-1}). Emissions from iLUC outweigh potential greenhouse gas (GHG) savings from fossil fuel substitution, except for Thailand, where increasing bioplastics production from sugarcane and cassava saves on average 2.0 kg CO_2-eq. t^{-1}. This translates into decades of carbon payback time and high abatement costs even for Thailand, while trade-offs arise among the metrics proposed. Other impacts besides deforestation and GHG emissions should ideally be considered to examine further interactions within the Water-Food-Energy nexus, though this may require combining global with regionalized approaches, with the associated challenges.

1. Introduction

Bioeconomy aims at improving the sustainability of production and consumption systems by replacing fossil fuels with biomass across industries (D'Amato et al., 2017; Ramcilovic-Suominen and Pülz 2018). If relying only on conventional agricultural feedstock, this poses the risk of increasing competition for land and water resources globally, with the associated environmental and social impacts (Liobikiene et al., 2019; Rosegrant et al., 2013). To prevent undesired spillover effects, bioeconomy strategies across the world are progressively shifting the focus away from fossil substitution towards more advanced technologies, integrated value chains and new business models (Escobar and Laibach, 2021; Golembiewski et al., 2015; van Lancker et al. 2016); e.g. the revised Bioeconomy Strategy of the European Union (EU) (European Commission 2018a). Well-designed policies and instruments still need to consider interactions across the Food-Energy-Water nexus, in order to minimize trade-offs and effectively contribute to the Sustainable Development Goals (SDGs) (Liu et al., 2018; Simpson and Jewitt 2019; Von Braun 2018). This requires advances in both data and tools to capture linkages between sectors and regions at multiple geographical scales (Liu et al., 2017; Sachs et al., 2019). As for the bioeconomy, new approaches are needed to monitor the long-term sustainability of interventions, including forward-looking models that capture further effects across food, feed, fuel and fibre markets (El-Chichakli et al., 2016; M'Barek et al., 2014; Rogers et al., 2017). Standardized metrics should also be proposed to communicate the economic, social and environmental impacts of such

* Corresponding author.
E-mail address: escobar@iiasa.ac.at (N. Escobar).

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interventions to both the public and decision-makers (Liobikiene et al., 2019; O'Brien et al., 2017). These metrics should ideally yield objective and comparable indicators across sectors and countries to support management and governance (Lainez et al., 2018).

At the product level, the environmental performance of bio-based production systems is often measured by means of Life Cycle Assessment (LCA), also compared with their fossil counterparts (Cheroennet et al., 2017; Cristóbal et al., 2016; Pawelzik et al., 2013). LCA combines bottom-up inventory data on input and output flows with standardized 'impact characterization methods' to estimate environmental impacts from 'cradle to gate' (grave). The methodology is still under development to consistently address the economic and social dimensions (Lainez et al., 2018; Mattila et al., 2018; Siebert et al., 2018). Traditional LCA considers technological systems in isolation, hence overlooking indirect effects through increasingly interconnected value chains, unless Consequential LCA approaches are applied. The latter aim at representing market-mediated adjustments to be triggered by changes in technology or demand, which commonly entails the application of economic equilibrium models (Dandres et al., 2011; Earles et al., 2013). Impacts embedded in production (consumption) can also be estimated at the sector or country level by using Environmentally-Extended Multi-Regional Input Output (EE-MRIO) analysis (Chen et al., 2018; Tukker et al., 2016; Weinzettel and Wood 2018). EE-MRIO models estimate downstream (upstream) resource use and emissions across the entire economy, up to final consumption; but do not consider substitution in input use, trade or final demand. The resulting environmental footprints give an indication of the global spillovers associated with supply- or demand-driven shocks, although conversion efficiencies, yields and trade relationships remain unaltered, similar to non-consequential LCA (Bruckner et al., 2015; Wiebe et al., 2018). Considering feedback effects among these factors is crucial to assess sustainability trade-offs –including food security–, and hence at the core of the Food-Energy-Water nexus (Humpenöder et al., 2018; O'Brien et al., 2017).

Global economic equilibrium models have also been used to quantify environmental impacts associated with an expansion in bio-based sectors, by considering competition for crops among other uses and further price-mediated responses (Escobar et al., 2018; Hertel et al., 2013). These models can be either partial or general equilibrium, depending on whether they depict the entire economy or only part of it. Their common features are that they a) rely on micro-economic theory to simulate producers and consumers' responses; and b) encompass global data on yields, firms' cost structures and bilateral trade. Computable General Equilibrium (CGE) models are especially suited for simulating land use leakage and spillovers from technological change and policy interventions, since these cover key economic mechanisms determining global price and yield responses, such as bilateral trade and production factor availability (Hertel 2018). As the most commonly discussed market-mediated impact in the context of biofuel policies, 'induced Land Use Change' (iLUC) refers to the subsequent land cover changes triggered by an increased demand for crop-based biomass for both traditional and alternative uses (Broch et al., 2013). ILUC translates into greenhouse gas (GHG) emissions from carbon stock changes and can undermine the GHG benefits of fossil fuel substitution (Hertel et al., 2010a; Taheripour et al., 2010). The net iLUC effect depends directly on the feedstock used, its production site and underlying agronomic conditions; but also indirectly on agricultural expansion and intensification adjustments. In spite of the advantages of CGE models to capture these mechanisms, major challenges still remain for measuring impacts related to the biophysical environment, such as the ability to trace flows in physical units or the level of spatial and sectoral disaggregation. Furthermore, the need for both large and consistent datasets and behavioural parameters to predict demand, supply and trade responses introduces data collection challenges as well as uncertainty in environmental impact results (Daioglou et al., 2020; O'Brien et al., 2017). Major advantages and limitations of the above-mentioned approaches to assess the sustainability of bio-based production are summarized in Table 1.

Table 1
Major approaches to estimate environmental impacts of bio-based production pathways at different levels, as well as associated advantages and limitations.

Methodology	Scope of analysis	Application	Advantages	Limitations
Life Cycle Assessment	Process or supply chain level	Estimation of environmental (social, economic) impacts of products, processes or services, from cradle to grave	a) Provides high level of detail in input and output flows (i.e. resources and emissions) based on bottom-up life cycle inventories b) Tracks resource and product flows between sub-processes in physical units, as well as at end-of-life c) Estimates multiple environmental indicators based on standardized impact characterization methods	a) Results are case-specific, based on average process conditions, and not necessarily representative for an entire sector b) Life cycle inventories are data-intensive and require data from both primary and secondary sources c) Characterization methods are still under development for the social and economic dimensions d) Overlooks impacts that occur outside the technological system
Environmentally-Extended Multi-Regional Input-Output analysis	Economy-wide	Estimation of emission and resource footprints embodied in consumption (production) at the country or sector level	a) Includes upstream (downstream) resource consumption across the entire economy, up to final demand b) Considers regional cross-sectoral effects from global bilateral trade c) Quantifies several environmental indicators when coupled with top-down biophysical extensions	a) Mostly relies on economic information: assumptions required to track flows in physical units b) Does not capture price-mediated adjustments across feedstock and factor markets and international trade c) Assumes fixed input structures, yields and trade relationships d) Level of detail in environmental footprints is limited by the regional and sectoral resolution in available databases (aggregation bias)
General economic equilibrium models	Economy-wide	Estimation of socioeconomic and environmental effects from technology- and policy-driven shocks in product and factor markets	a) Provide a consistent representation of the entire economy based on micro-economic theory, including bilateral trade b) Simulate market-mediated effects due to changes in feedstock and factor prices c) Consider substitution between intermediate inputs and endowments, including energy and land d) Quantify land and greenhouse gas (GHG) emissions across the economy, if coupled with biophysical extensions and emission modules	a) Environmental modules focus on Land Use Change, GHG emissions and other emissions to air b) Not possible to trace resource flows in physical units c) Results are derived from assumptions and parameters to model producers' and consumers' responses d) Level of detail in environmental and socioeconomic outcomes is limited by regional and sectoral resolution in available databases (aggregation bias)

As for the metrics, the GHG performance of bio-based pathways is frequently quantified as CO_2-eq. per unit of product, e.g. per MJ in the case of biofuels (Capaz et al., 2021; Daioglou et al., 2017). When emissions from iLUC are included, these metrics are often referred to as 'iLUC factors' (Laborde and Valin 2012; Malins et al., 2020). The European Union (EU), for instance, introduces "iLUC-risk factors" into its revised Renewable Energy Directive (European Commission, 2018b) for biofuels to be used in the EU market, based on previous model-based evidence. The estimation of such metrics is however associated with uncertainty due to variability in underlying CGE model parameters, or *epistemic* uncertainty according to Plevin et al. (2010); as well as in modelling choices or *decision* uncertainty, e.g. on the amortization period for iLUC emissions. Specifically, parameter variability is a great contributor to the uncertainty in iLUC factors of biofuels when quantified with CGE models (Plevin et al., 2015). 'Carbon payback time' is another common metric in the biofuel literature and refers to the number of years required for GHG savings due to fossil fuel substitution to offset CO_2 emissions from land conversion (Fargione et al., 2008; Gibbs et al., 2008). Most carbon payback time estimates focus on carbon stock losses on the site where biofuel feedstock is produced, by defining foreseeable land use scenarios (as for crop location, management and productivity) and spatially-explicit carbon pools in soil (Gibbs et al., 2008; Mello et al., 2014), or both in soil and biomass (Elshout et al., 2015;2019). In a recent study, Escobar et al., (2018) quantified carbon payback times associated with an increased consumption of crop-based bioplastics on a global scale, by including GHG emissions from iLUC based on CGE modelling. The present study complements the work of Escobar et al., (2018) to provide further insights on the sustainability of bioplastics production, considering global competition for feedstock and associated market-mediated responses. The objective is threefold:

a) to define a suite of quantitative indicators on the sustainability of emerging sectors in the bioeconomy, which capture global spillover effects in terms of iLUC, GHG emissions, fossil fuel extraction and GDP.
b) to estimate and compare the proposed indicators for an increased production of bioplastics in major producing regions, simulated through region-specific production subsidies.
c) to assess the uncertainty in outcome metrics by considering different levels of market penetration of bioplastics as well as variability in key model parameters.

2. Methods

2.1. Database extension

This study departs from the work of Escobar et al., (2018), who extended the GTAP 9 database (Aguiar et al., 2016) to include *fossil-based plastics* and *bio-based plastics* as two differentiated sectors in the EU, United States (US), China and Brazil. These regions were selected based on their market shares in the year 2013, as the leading bioplastic producers on a global scale. Given the small sizes of emerging bio-based sectors, it is important to focus on countries that account for significant market shares in the base year, such that a relative increase in their size produces plausible results in global CGE analysis. In addition to the aforementioned regions, this study also includes Thailand, even though its current market share is relatively much smaller (Table 2). Yet, Thailand is expected to become a leading global producer of biodegradable and bio-based plastics in view of the significant investment in the last years (Fielding and Aung 2018; OECD 2013), which renders it an interesting case study to estimate associated sustainability risks. As shown in Table 2, the five regions together represent 70.27% of the total plastic market in the base year, while bioplastics only account for 0.20% of it. Relative bioplastics production capacities in Table 2 are consistent with estimations of Ifeu (2013), as well as with the market share of biopolymer production in the EU in 2019, i.e. 0.40% of the total EU's plastic production (IEA, 2020). The estimated output shares were used to disaggregate *fossil-based plastics* and *bioplastics* from the original chemical sector in GTAP 9, by means of the split utility developed by Britz and van der Mensbrugghe (2018). The cost structure of the newly created bioplastic sector was also adjusted to represent the different input requirements relative to conventional plastic production. Moreover, the production structure in the standard GTAP model (Hertel 1997) had to be modified to capture how easily firms substitute bioplastics for conventional ones as intermediate inputs, according to a Constant Elasticity of Substitution (CES) function – see section S1 of the Electronic Supplementary Material (ESM) and Escobar et al., (2018) for further information.

Table 2
Each region's share of the global bioplastic and total plastic markets (%) in the benchmark year; and associated cost shares (%) in bioplastic production. EU28: European Union.

	Brazil	China	EU28	Thailand	United States
Bioplastic market share of the world's output (%)	33.33%	16.22%	28.23%	2.70%	19.52%
Total plastic market share of the world's output (%)	3.54%	23.99%	25.60%	1.12%	16.02%
Bioplastics market share of total plastics output (%)	1.90%	0.14%	0.22%	0.49%	0.25%
Cost shares in bioplastic production (%)					
Raw material	17.10%	35.00%	18.80%	17.00%	17.10%
Rest of intermediate inputs	28.70%	30.80%	33.20%	20.20%	30.00%
Primary factors	50.40%	33.70%	39.80%	62.10%	47.90%
Input taxes	3.80%	0.50%	8.10%	0.70%	5.00%

Same as Escobar et al., (2018), only biopolymers made from starch and sugar crops are considered here, since these are the only ones that are currently cost-competitive with fossil-based polymers and produced in significant amounts. More advanced technologies, e.g. based on lignocellulosic or algal biomass, are not yet commercially available (Brodin et al., 2017; Govil et al., 2020). It was assumed that Brazil's production of bioplastics consists of 98% of bio-polyethylene (bio-PE) plus a small share of polyhydroxybutyrate (PHB), both from sugarcane. The EU employs wheat and maize in similar amounts for the production of thermoplastic starch (TPS) blends (ca. 99%) and a small share of polylactic acid (PLA). China and the US produce PLA, PHB and polyhydroxyalkanoate (PHA) mainly from maize and wheat. Thailand uses sugarcane and cassava to produce Polybutylene Succinate (PBS), while projected PLA plants were not yet in operation in 2013 (Shen et al., 2009). In order to achieve this level of product detail in bioplastic feedstock, maize and cassava were disaggregated in the GTAP 9 database in the same way as bioplastics; in this case, from the sectors 'cereal grains' and 'fruits and vegetables', respectively. Output and trade shares for the split were obtained from an EE-MRIO model with a high level of detail in agro-food commodities (Bruckner et al., 2019), which also provided information on the cost shares. The resulting database has 61 sectors and 140 regions (later

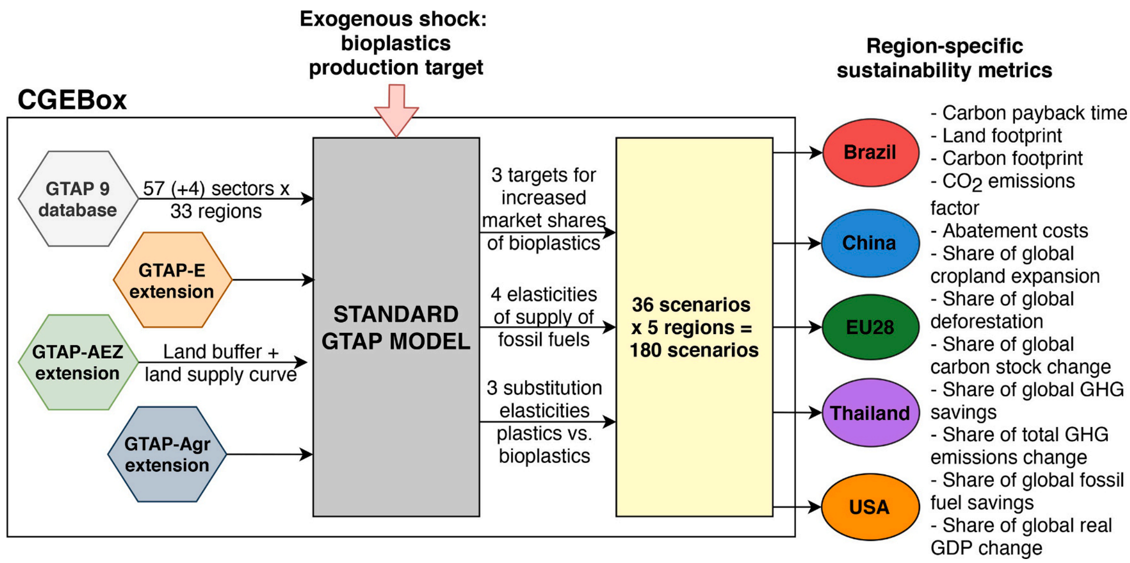

Fig. 1. Methodological framework for estimating metrics on the sustainability of bioplastics production at the region level, based on the model of the Global Trade Analysis Project (GTAP) as implemented in the flexible, extendable, modular and open-source tool CGEBox.[1]

aggregated into 33 regions), depicting the world economy in 2011, and is taken as the benchmark.

2.2. Modelling framework

The analysis was carried out with the flexible and modular platform for CGE modelling 'CGEBox' (Britz and van der Mensbrugghe 2018). The methodological approach is summarized in Fig. 1, which also highlights the contribution of this study with regard to database preparation, model extension and systematic uncertainty analysis within the CGEBox framework. The methodology relies on several extensions of the standard GTAP model, namely: GTAP-Agr (Keeney and Hertel 2005), which improves the representation of agricultural markets and production technologies; GTAP-E (Burniaux and Truong 2002), which allows substituting among energy sources and between energy sources and other factors in the production structure of firms, while calculating CO_2 emissions from energy consumption across sectors. Non-CO_2 emissions (i.e. N_2O, CH_4) from agricultural and livestock production and endowment use were included according to Aguiar et al., (2016). The GTAP-AEZ module (Lee 2005) was also used to simulate land transformation across 18 Agro-Ecological Zones (AEZs) (Fischer et al., 2012). The original GTAP-AEZ extension differentiates the three major productive uses of land, i.e. cropland, pastureland and managed forestland. In each AEZ, each use is associated with area-based carbon stocks in soil, above- and below-ground biomass, and litter (Gibbs et al., 2014). In this way, land conversion from one use to the other ultimately translates into CO_2 increases (decreases) when carbon stocks decrease (increase) relative to the previous land use. In order to improve the representation of iLUC, GTAP-AEZ was further extended to include natural cover loss to agricultural and forestry production by implementing the so-called "land supply curve" approach (Van Meijl et al. 2006); as combined with a buffer of land areas suitable to be converted into agriculture at the region level, based on Eitelberg et al., (2015). The land supply curve simulates increased (decreased) land supply as a function of the average land rental rate in each region, governed by a land supply elasticity. The land buffer also includes areas of unmanaged forest, savannah, grassland, shrub land and other land (see section S1 in the ESM).

Comparative-static CGE analysis is applied to examine the effects of an exogenous *shock* on the economy (e.g. a policy or technological change), by determining the changes in model variables necessary to find a new equilibrium in which all markets clear. Impacts are thus measured as the difference in output variables vis-à-vis original values in the base year, i.e. 2011, without providing information on the transition path from the original equilibrium. In this case, the experiment consists of exogenously increasing bioplastic production in each region separately, representing a bioplastic production target. Following the example of biofuel mandates, this is done by introducing a production subsidy or tax exemption (Hertel et al., 2010b; OECD 2014). In each simulation, production taxes (i.e. subsidies to bioplastic producers) adjust endogenously to reach the desired level of production. The bioplastic target is here defined as a market share of the regional plastic market to be replaced with bioplastics, since the two kinds of plastics are treated as imperfect substitutes in consumption. In other words, the target increases the market share of bioplastics at the cost of conventional plastics in the region of study, while the production of both bio- and fossil-based plastics in the rest of the world (ROW) remains constant. The absolute increase in bioplastics production thus depends on each region's share of the total plastic market in the base year (Table 2). The larger the share, the more pronounced the market-mediated effects to be expected. In CGE analysis, this does not necessarily translate into greater impacts due to underlying feedback effects, which in turn arise from the competition for limited resources among all economic sectors.

2.3. Scenario assumptions for the uncertainty analysis

The approach summarized in Fig. 1 allows sustainability metrics to be estimated at the sector and region level. In every scenario, changes in the environmental and socioeconomic indicators assessed are only due to an increase in bioplastics production in the corresponding region, *ceteris paribus*, but considering subsequent market-mediated effects that take place on a global scale. These changes depend directly on the level of increase relative to the benchmark, but also on values of the many model parameters. In order to understand uncertainty in sustainability outcomes due to both methodological choices and parameter variability, different scenarios were defined, by changing the production target as well as two parameters identified as critical (see Fig. 1). Firstly, three different levels of bioplastics production were considered, to reach a 1%, 5%, and 10% share of the total plastic market, respectively. It must be noted that CGE model outcomes do not vary proportionally with the size of the shock, due to the non-linear nature of the underlying market

[1] Model documentation and updated features can be found at: https://www.ilr.uni-bonn.de/em/rsrch/cgebox/cgebox_e.htm.

responses. Secondly, alternative values were defined for the elasticity of substitution between fossil-based plastics and bioplastics in firms' demand (ESUBST). This parameter measures how easily firms can replace fossil-based plastics with bioplastics as intermediate inputs, and hence determines the absolute increase in bioplastic production necessary to fulfil the target. An initial value of 15 was assumed (Escobar et al., 2018), which constitutes a relatively high elasticity of substitution due to the large share of drop-in products in the base year. Two additional values (5 and 10) were considered based on Nowicki et al., (2010), to represent increasing market shares of non-drop-ins such as PLA (Aeschelmann and Carus 2015; IfBB 2019). Finally, different values were assumed for the price elasticity of supply of fossil fuel resources (ESUPP) (0, 0.1, 0.5 and 1), to provide a range around default GTAP values. This parameter determines how responsive the supply of coal, crude oil and natural gas is to price changes triggered by the reduced demand for fossil resources in the plastic industry. All these choices yield 36 scenarios per region and 180 scenarios in total.

2.4. Calculation of sustainability metrics

Changes in CGE model outcomes in terms of land uses (in ha), GHG emissions (as kg CO_2-eq.), fossil fuel extraction (in constant US$) and real GDP (in constant US$), relative to the benchmark, were employed to define a suite of sustainability metrics at the region level. It must be borne in mind that, in CGE analysis, iLUC effects are the result of both agricultural land expansion to directly grow bioplastic feedstock and further price-induced land transformation effects. The metrics are calculated with the equations detailed below Eqs. (1)-(12), although additional metrics could be considered (see section S2 in the ESM).

- Land footprint (ha t^{-1}) as the net area change across all land uses that takes place on a global scale (i.e. iLUC) per additional unit of bioplastic produced in the region of study

$$Land\ footprint_x = \frac{\sum_r \left(\Delta Cropland_r + \Delta Pasture_r + \Delta Forest_r + \sum_z \Delta Unmanaged_{r,z}\right)}{\Delta Qbiop_x} \tag{1}$$

Where (x) refers to the region where bioplastics production increases, (r) refers to all regions in the world[2], and (z) refers to the different unmanaged land uses considered in the database, namely, unmanaged forest, grassland, savannah, shrub land, and other land. $Qbiop_x$ is the absolute increase in bioplastics production in the region of study (x) in tonnes, relative to the benchmark production capacities.

- Carbon footprint (kg CO_2-eq. t^{-1}) as the annual change in global GHG emissions (excluding emissions from iLUC) per additional unit of bioplastic produced in the region of study, as an indication of the carbon intensity of bioplastics produced in that region

$$Carbon\ footprint_x = \frac{\sum_r (\Delta CO2_r + \Delta nonCO2_r)}{\Delta Qbiop_x} \tag{2}$$

Where $\Delta CO2_r$ and $\Delta non\text{-}CO2_r$ refer to the annual changes in GHG emissions (as CO_2-eq.) from energy consumption and endowment use across industries and regions (r).

- CO_2 emission factor (kg CO_2-eq. t^{-1}) as the annual change in global GHG emissions (including emissions from iLUC) per additional unit of bioplastic produced in the region of study, as a measure of the total carbon footprint of bioplastics produced in that region

$$CO2\ em.\ factor_x = \frac{\sum_r \left(\Delta CO2_r + \Delta nonCO2_r - \Delta CStock_r \times \frac{44}{12} \Big/ 20\right)}{\Delta Qbiop_x} \tag{3}$$

Where $\Delta CStock_r$ refers to the net changes in land carbon stocks across all regions (r) caused by the increase in bioplastics production in the region of study.

- Carbon payback time (years) as the time that it takes for the global GHG savings from replacing fossil-based plastics with bioplastics to compensate for the total CO_2 emissions from iLUC as a one-time effect

$$Carbon\ payback\ time = \frac{\sum_r \Delta CStock_r \times \frac{44}{12}}{\sum_r (\Delta CO2_r + \Delta nonCO2_r)} \tag{4}$$

- Annual abatement costs of the bioplastic production target (US$ t^{-1} CO_2-eq.) as the ratio of the annual change in real GDP in the region of study to the annual change in global GHG emissions (including annualized emissions from iLUC, by considering an amortization period of 20 years)

$$Abat.\ costs_x = \frac{\Delta GDP_x}{\sum_r \left(\Delta CO2_r + \Delta nonCO2_r - \Delta CStock_r \times \frac{44}{12} \Big/ 20\right)} \tag{5}$$

Abatement costs are estimated based on reductions in real GDP due to the economic distortion induced by the target in each region (relative to the original market equilibrium), and should not be understood as a burden on taxpayers only.

[2] The set (x) is a subset of (r).

- Share of the global cropland expansion (SGCEx): ratio of the net change in cropland area in the region of study to the net change in cropland area on a global scale (%), as a measure of the cropland leakage

$$SGCEx_x = \frac{\Delta Cropland_x}{\sum_r \Delta Cropland_r} \tag{6}$$

- Share of the global deforestation (SGDef): ratio of the net area change across unmanaged land uses in the region of study to the net area change across unmanaged land uses on a global scale (%), as a measure of the deforestation leakage

$$SGDef_x = \sum_z \Delta Unmanaged_{x,z} \Big/ \sum_{r,z} \Delta Unmanaged_{r,z} \tag{7}$$

- Share of the global carbon stock change (SGCarb): ratio of the of the change in land carbon stocks due to iLUC in the region of study to the change in land carbon stocks on a global scale (%), as a measure of the carbon leakage

$$SGCarb_x = \frac{\Delta CStock_x}{\sum_r \Delta CStock_r} \tag{8}$$

Where $\Delta CStock_x$ refers to the net change in land carbon stocks in the region of study (x) and $\Delta CStock_r$ refers to the net changes in land carbon stocks across all regions (r).

- Share of the global GHG savings (SGHGSav): ratio of the of the annual change in CO_2 and non-CO_2 emissions from energy consumption and endowment use in the region of study to the annual change in global GHG emissions (%), as a measure of the GHG leakage (without iLUC emissions)

$$SGHGSav_x = \frac{\Delta CO2_x + \Delta nonCO2_x}{\sum_r (\Delta CO2_r + \Delta nonCO2_r)} \tag{9}$$

Where $\Delta CO2_x$ and Δnon-$CO2_x$ refer to changes in GHG emissions from energy consumption and endowment use across industries in the region of study (x) and $\Delta CO2_r$ and Δnon-$CO2_r$ refer to the annual changes in GHG emissions across all industries and regions (r).

- Share of the total GHG emission change (STGHG): ratio of the of the annual change in total GHG emissions (including annualized emissions from iLUC) in the region of study to the annual change in total GHG emissions (%), by considering an amortization period for iLUC emissions of 20 years

$$STGHG_x = \frac{\Delta CO2_x + \Delta nonCO2_x - \Delta CStock_x \times \frac{44}{12} \Big/ 20}{\sum_r \left(\Delta CO2_r + \Delta nonCO2_r - \Delta CStock_x \times \frac{44}{12} \Big/ 20 \right)} \tag{10}$$

- Share of the global fossil fuel savings (SGFFuel): ratio of the change in fossil fuel production in the region of study to the change in fossil fuel production across the world (%), as a measure of the fossil depletion leakage

$$SGFFuel_x = \frac{\sum_f \Delta Sfoss_{f,x}}{\sum_{f,r} \Delta Sfoss_{f,r}} \tag{11}$$

Where $Sfoss_{f,x}$ covers the supply of all fossil fuels (f) (i.e. coal, gas and crude oil) in the region of study (x) and $Sfoss_{f,r}$ covers the supply of all fossil fuels across all regions (r).

- Share of the global real GDP change (SrGDP): ratio of the of the change in real GDP in the region of study to the change in global real GDP (%), as a measure of the GDP loss leakage

$$SrGDP_x = \frac{\Delta GDP_x}{\sum_r \Delta GDP_r} \tag{12}$$

3. Results

In each region and scenario, the bioplastic target produces different market responses across the economy, which translates into variability in sustainability metrics. The associated distributions differ in spread and shape due to the non-linear adjustments in model variables triggered by the target in the various scenarios considered. The bioplastic target causes an increase in demand for feedstock in the region of study, which is met with a mix of domestic and imported raw materials, according to its trade structure. As *immediate effects* (see Fig. 2), this drives up crop prices and land rents in grain and sugar producing and exporting regions, causing cropland expansion and ultimately iLUC and GHG emissions globally. Substitution for fossil-based plastics translates into a lower demand for fossil fuels in the bioplastic producing region and subsequent GHG savings, which can be interpreted as *side effects*. Rebound effects can also occur through decreases in fossil fuel prices, potentially resulting in an increased demand for fossil fuels in some regions. Such rebound effects are however expected to be minor given the kind of shock. The larger the simulated increase in bioplastics production in absolute terms, the stronger both the immediate and side effects due to the greater demand for feedstock and associated price changes. As seen below, this does not necessarily imply higher values of the outcome metrics due to the underlying market feedback effects.

The results vary widely across regions and scenarios. As observed in Fig. 3 (corresponding to Eqs. (1)–(5)) and Fig. 4 (Eqs. (6)–(12)), none of the regions offers clear sustainability advantages over the others, while trade-offs arise among the metrics considered. Only bioplastics production in Thailand delivers more favourable indicators in terms of iLUC, GHG emissions and associated spillovers. However, this is related to the very small increase in bioplastics production as compared to the other regions, which translates into minor market-mediated responses (see Table 2). On the contrary, in China, the increase in bioplastics production necessary to meet the target is the largest in absolute terms, given the sizes of both its plastic and bioplastic markets in the base year. As a result, bioplastics production in China is associated with larger land footprints than the other regions (Fig. 3a). The average land footprint of Chinese bioplastics is estimated at 16.93 ha per additional tonne of bioplastic delivered to the market; while it is 2.9 ha, 1.1 ha and 3.94 10^{-2} ha for the EU, the US and Thailand, respectively. The average land

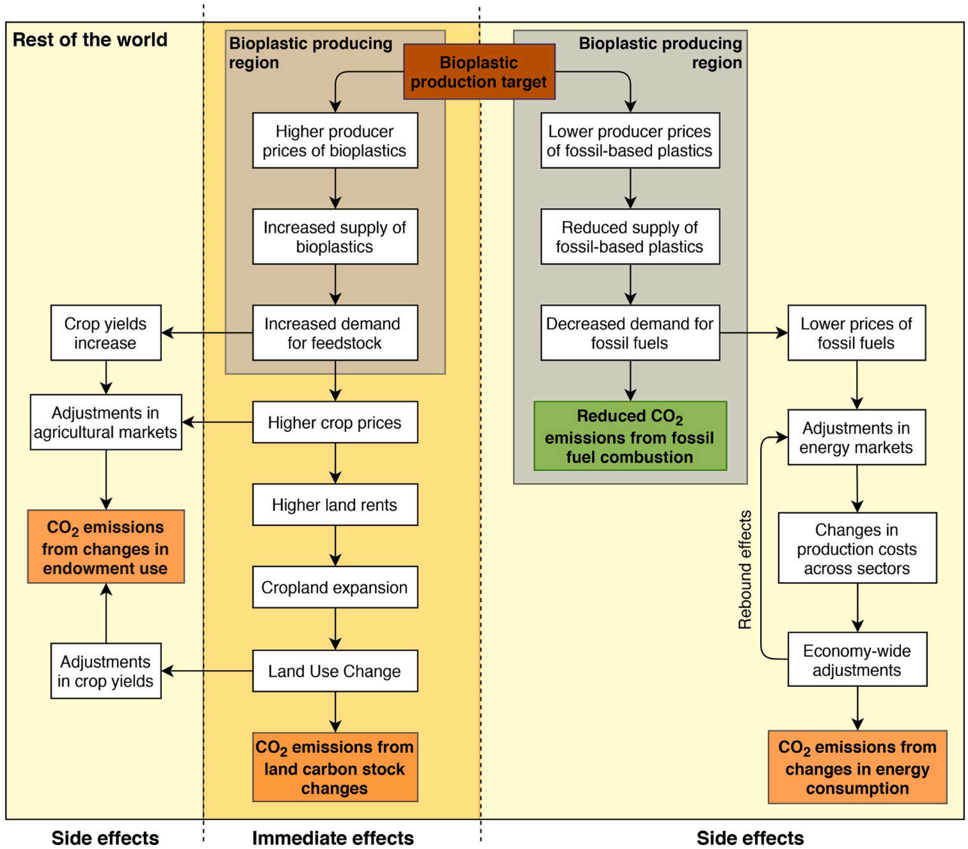

Fig. 2. Market responses triggered by the bioplastic production target in the bioplastic producing region and on a global scale. Immediate effects refer to price-mediated adjustments across bioplastics and related feedstock markets. Side effects propagate across the rest of the economy through price-mediated adjustments in fossil-based plastic markets.

footprint is even negative for Brazil (-2.5 10^{-2} ha), implying a net contraction of the global land area through iLUC. On the contrary, when the carbon footprint is estimated without iLUC emissions, bioplastics produced in China are associated with greater GHG savings (Fig 3b), since the bioplastic target generates a greater contraction of the fossil-based plastic market. Average carbon footprints are negative across regions, hence supporting the idea that bioplastics contribute to climate mitigation. Specifically, values are below 0 across the entire distribution of carbon footprints for China and Brazil, with average values of -12,886 kg CO_2-eq. t^{-1} and -17.9 kg CO_2-eq. t^{-1}. In the EU, US and Thailand, some of the scenarios simulating a 1% target generate positive carbon footprints, although average values are -1,066.2 kg CO_2-eq. t^{-1}, -93.7 kg CO_2-eq. t^{-1} and -16.5 kg CO_2-eq. t^{-1}, respectively.

When iLUC emissions are annualized and included in the carbon footprint, most scenarios generate net GHG emissions instead of savings per tonne of bioplastics (Fig. 3c). The highest CO_2 emission factors are found for China and the EU, where the target generates greater market-mediated responses given the size of the shock. The EU shows on average the highest CO_2 emission factor (10,405 kg CO_2-eq. t^{-1}). This is related to the size of its bioplastic market in the base year and its trade structure, as EU bioplastics production relies on imports to a greater extent than China's, leading to greater price adjustments in international food markets. The variability in CO_2 emission factors is however wider for China than for the EU. Specifically, values range from -1,199 to 15,208 kg CO_2-eq. t^{-1}, with an average value of 6,620 kg CO_2-eq. t^{-1}. Both the highest and lowest values correspond to the 10% target, but associated with different combinations of ESUPP and ESUBST. While ESUPP=0 and ESUBST=15 yield the highest emission factor, ESUPP=1 and ESUBST=5 deliver the lowest. As expected, the higher the ESUBST the greater the reduction in fossil-based plastics output and the subsequent decrease in GHG emissions. However, the latter also depends on the effects on the supply of fossil fuels, which are more noticeable with ESUPP=1 than with any of the other values considered. CO_2 emission factors are much lower for Brazil (<133 kg CO_2-eq. t^{-1}) and the US (<1,325 kg CO_2-eq. t^{-1}) than for China and the EU, but the only country in which bioplastic production translates into global GHG savings is Thailand. The average emission factor is -2.0 kg CO_2-eq. t^{-1}, with a minimum value of -18.7 kg CO_2-eq. t^{-1}. However, these figures would change if larger absolute increases in bioplastics production were simulated, with greater iLUC effects to be expected.

Carbon payback times provide another perspective for estimating potential GHG risks associated with bioplastics production in each region, considering iLUC. Although this metric is related to the CO_2 emission factors described above, there is disparity in the results from a comparative point of view (Fig. 3d). It must be noted that a payback time only exists if the value is above 0, which implies that economy-wide GHG emissions decrease annually to offset CO_2 emissions from global LUC as a one-time effect (see Eq. (4)). The payback time thus indicates the minimum period for the production subsidy to remain in place in order to start delivering actual GHG savings on a global scale, at the cost of annual GDP losses and other economic impacts. Negative payback times correspond to scenarios in which both carbon stocks are lost globally and CO_2-eq. emissions from economic activities increase. Such counterproductive outcomes for climate change mitigation are only found in some scenarios corresponding to the EU and US.

The longest (average) carbon payback time is quantified for the EU (232.5 years), followed by Brazil (171.8 years). This shows that sustainability outcomes do not only depend on the level of market substitution but also on the subsequent market-mediated responses (Fig. 3d). Longer payback times indicate that increasing bioplastics production in those regions poses a greater risk of carbon-rich ecosystems being lost on a global scale. The main difference is that in Brazil deforestation occurs

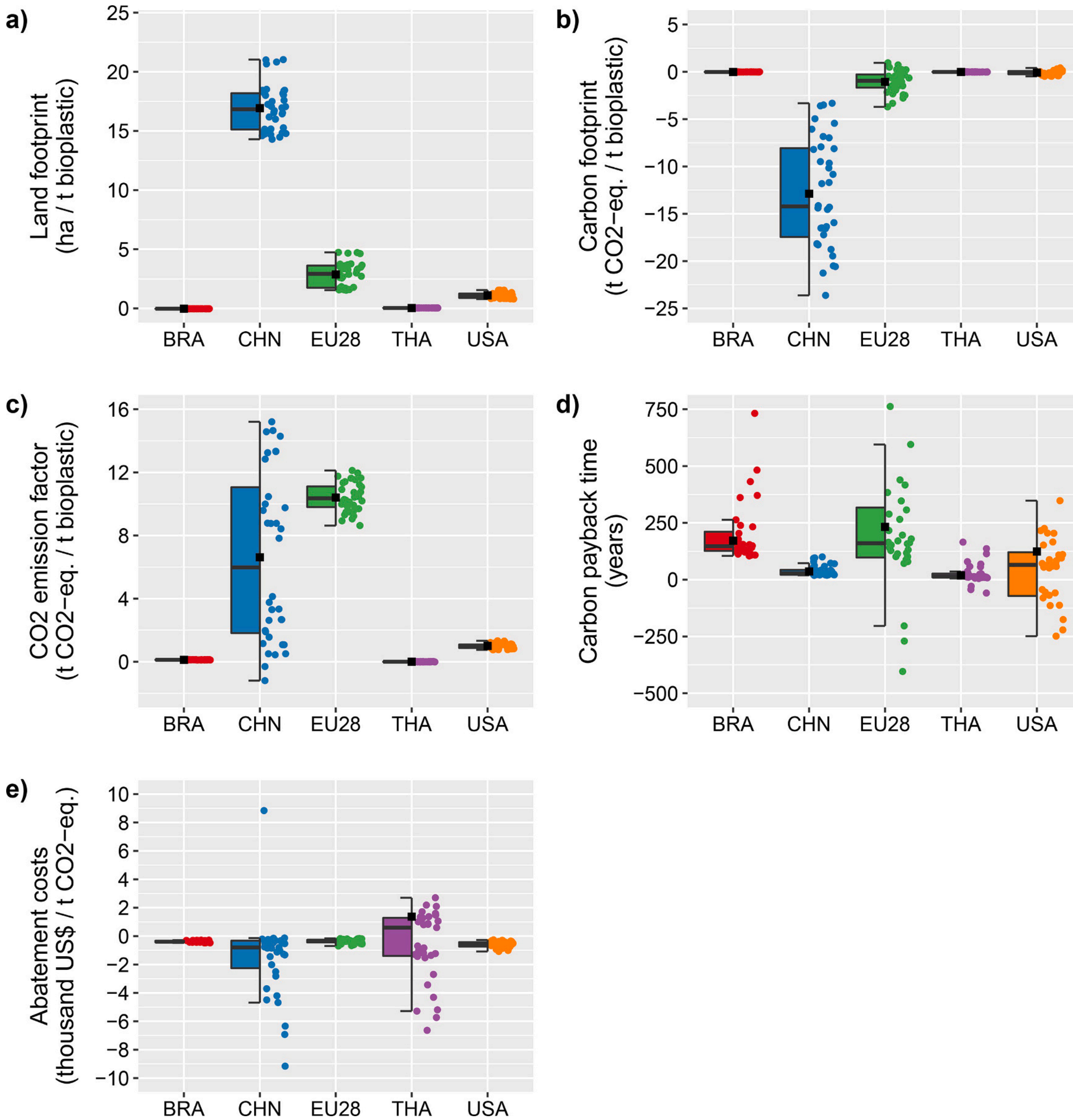

Fig. 3. Distribution of region-specific land footprints (a), carbon footprints (b), CO_2 emission factors (c), carbon payback times (d) and annual abatement costs (e). Black dots indicate the mean. Values below Q1 - 1.5 x IQR and above Q3 + 1.5 x IQR are considered outliers and excluded. For carbon payback times (d) and abatement costs (e) only the mean of the positive values is shown. If no mean value is indicated, this implies that all values are negative. BRA: Brazil; CHN: China; EU28: European Union; THA: Thailand; USA: United States.

mainly within the country, while the bioplastic target in the EU generates greater deforestation in the ROW, as a market-mediated spillover (Fig. 4b). In fact, an increased production of bioplastics in Brazil leads to a greater cropland expansion in the country itself than on a global scale in 66.7% of the scenarios (Fig. 4a). The greater variability is however found for the EU and US payback times, which is related to the fact that the target in both regions generates deforestation leakage (Fig. 4b). In the US, the target takes on average 124.1 years to deliver net GHG savings on a global scale, while in China, it takes 36.1 years, as a result of the greater annual GHG savings through reduced fossil fuel consumption. The shortest carbon payback times are estimated for Thailand, with an average value of 18.6 years (Fig. 3d). This is because of the relatively smaller increase in bioplastics production, which generates moderate carbon losses in relation to annual GHG savings. Same as in Brazil, most of these carbon losses arise from natural vegetation loss within the country (Fig. 4b,c).

The metric in Eq. (5) can only be interpreted as actual abatement costs if values are positive (Fig. 3e), which implies that GHG emissions decrease globally over a 20-year period, also considering iLUC emissions. Only the target in Thailand is associated with abatement costs –in half of the scenarios–, with an average value of 1,367.8 US$ t^{-1} CO_2-eq. In the other regions, a bioplastic target imposed via a production subsidy translates into increased GHG emissions globally at the cost of real GDP losses. As expected, the decrease in real GDP is especially sharp in China, where the largest increase in bioplastic production is needed, in absolute terms, to meet the target. Increasing the market share of bioplastics at the expense of conventional plastics production significantly reduces the demand for fossil fuels in China, with the subsequent contraction in fossil fuel industries. This ultimately generates a relocation of production factors (capital, labour) between the various sectors, with the subsequent increases in production costs, especially in the country itself but also abroad (see Fig. 2).

Metrics in Fig. 4 provide an indication of the spillover effects of the target as a relation between the effects in the country of study and the ROW. The lower the ratios, the greater the spillover effects. Hence, these metrics help to understand mechanisms that may not be so evident in

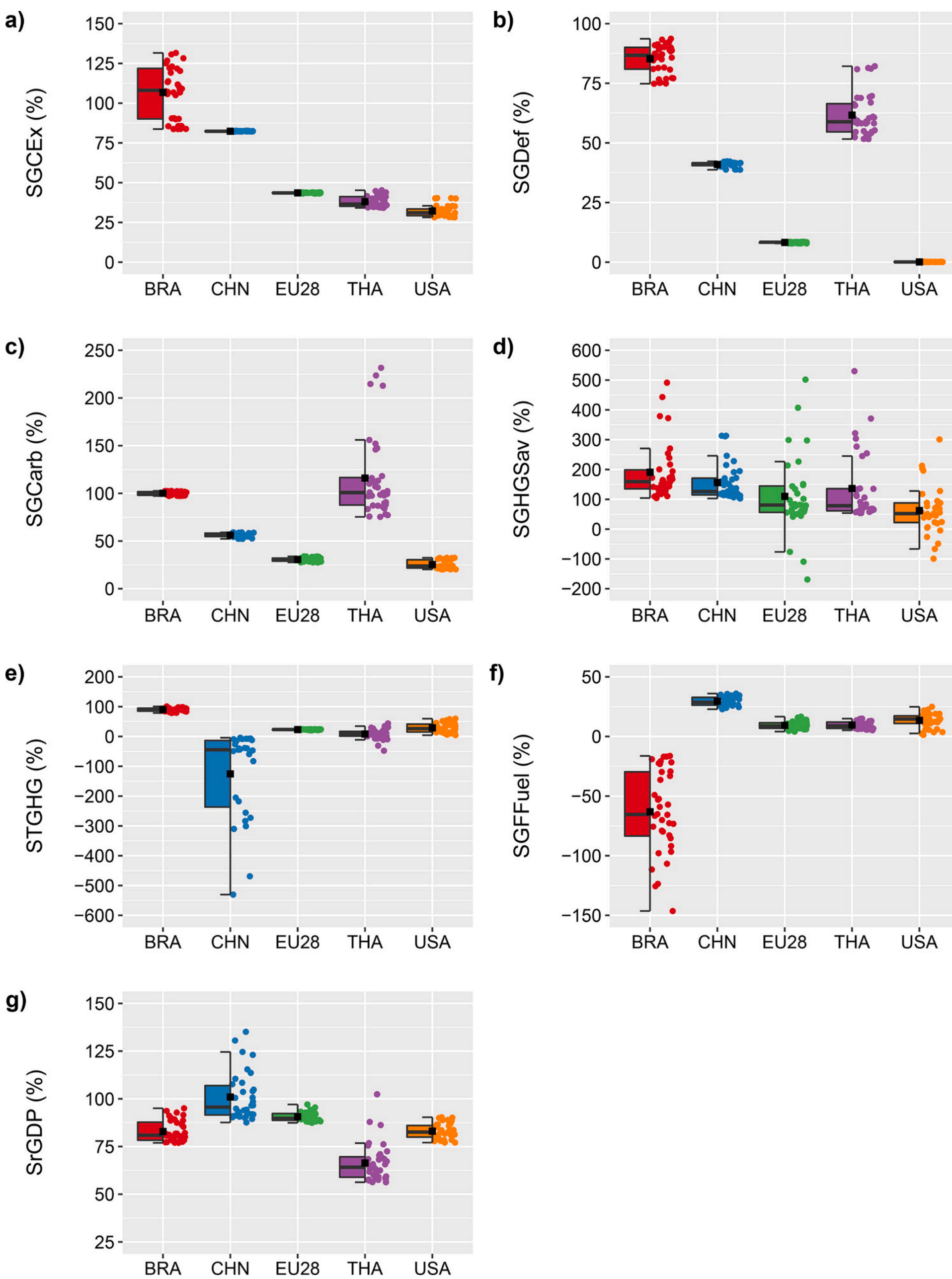

Fig. 4. Distribution of region-specific metrics (%) proposed for the *share of the global cropland expansion* (SGCEx) (a), *share of the global deforestation* (SGDef) (b), *share of the global carbon stock change* (SGCarb) (c), *share of the global greenhouse gas savings* (SGHGSav) (d), *share of the total greenhouse gas emission change* (STGHG) (e), *share of the global fossil fuel savings* (SGFFuel) (f), and *share of the global real GDP change* (SrGDP) (g). Black dots indicate the mean. Values below Q1 - 1.5 x IQR and above Q3 + 1.5 x IQR are considered outliers and excluded. BRA: Brazil; CHN: China; EU28: European Union; THA: Thailand; US: United States. Black dots indicate the mean. Values below Q1 - 1.5 x IQR and above Q3 + 1.5 x IQR are considered outliers and excluded.

Fig. 3, but are equally important for bioplastics production to deliver sustainability gains on a global scale. For instance, the smaller the SGCEx, the larger the land area converted into agriculture in the ROW (Fig. 4a). This constitutes land use leakage and can translate into further negative environmental and social impacts in other regions than those that subsidize bioplastic production. The EU, China and US are associated with greater spillover effects in terms of deforestation and carbon stock losses than Brazil and Thailand. The average SGDef ratios are the lowest for the EU (8.3%) and US (0.1%), which implies that more than 90% of natural vegetation loss due to the target in these two regions takes place abroad (Fig. 4b). In the EU, this is related to the relatively limited availability of natural land areas to be converted into agriculture in the land buffer (see Fig. S2). In the US, agricultural land expansion comes largely at the expense of managed forest, given the large areas of "accessible forest" in the original database (Baldos 2017). On the contrary, average SGDef ratios are estimated at 85.3% and 61.7% for Brazil and Thailand, respectively, where larger forestland areas are lost domestically. These involve carbon-rich ecosystems, as shown by the SGCarb, which is the largest again for these two countries, with average values above 100% in the two cases (Fig. 4c). Average SGCarb ratios are 56.2% and 30.5% in China and the EU, respectively, where carbon stocks are relatively small compared to other regions in the ROW. Further information on iLUC effects is included in the ESM (section S3).

The average SGHGSav is above 100% (Fig. 4d) in all regions except for the US, which indicates that the greatest GHG savings take place in the region where the target is set. In the EU and US, there is a larger share (>65%) of values below 100%, showing that these two regions partly outsource carbon intensive activities upstream the bioplastics supply chain. Accordingly, the target generates notable GHG savings from fossil substitution in the ROW. When including emissions from iLUC, all values of the STGHG in China are below 0%, which implies an emission spillover, i.e. GHG emissions decrease domestically but increase globally (Fig. 4e), except for one scenario (5% target; ESUPP=1; ESUBST=5) in which global GHG also decrease. This is due to the significant reduction in China's fossil fuel demand in combination with relatively moderate increases in iLUC emissions in the ROW. Spillovers are again detected for the US and the EU, since greater GHG emission increases take place globally than domestically. The target in Thailand is associated with much smaller changes in GHG emissions than the other countries, which translates into both positive and negative spillovers depending on the scenario. In half of them, GHG emissions decrease domestically and especially on a global scale; while in the rest, GHG emissions increase globally. On the contrary, the average STGHG is the largest for Brazil (90.5%), where deforestation is a major contributor to domestic GHG emissions.

Additional spillovers arise in terms of fossil fuel extraction and real GDP loss. The SGFFuel is negative in Brazil across scenarios (Fig. 4f), which means that fossil fuel extraction increases in Brazil and decreases globally. This can be understood as a rebound effect of the target, which decreases fossil fuel prices in Brazil and promotes exports (see Fig. 2). For the remaining regions, fossil fuel extraction decreases domestically and mostly on a global scale due to the lower fuel prices in the international market. Finally, the SrGDP is larger in China than in the other regions, with an average SrGDP of 102.9%. The loss in real GDP in the EU, US, Brazil and Thailand accounts on average for between 64% and 91% of the global real GDP loss (Fig. 4g). In the way it is defined, the target produces greater GDP losses in the region of study than abroad in all cases (SrGDP $>$ 50%). In absolute terms, average real GDP losses caused by the target on a global scale are estimated at US\$3.6 billion for China; US\$7.5 billion for the EU; US\$5.5 billion for the US; US\$1.7 billion for Brazil; and US\$0.3 billion in Thailand.

4. Discussion

The results described above confirm, on the one hand, the need to consider market-mediated effects when analysing the sustainability of crop-based commodities, such as bioplastics and biochemicals (Escobar et al., 2018; Nong et al., 2020). However, these effects must necessarily be simulated, with the associated uncertainty that depends not only on the modelling approach but also on the scenario definition and model variables (Plevin et al., 2010;2015; Searchinger et al., 2015). On the other hand, the multi-metric assessment reveals trade-offs among the indicators considered, even though these focus mainly on iLUC, GHG emissions and real GDP. For instance, increased bioplastic production in the EU may have a relatively lower land footprint (Fig. 3a) compared to China, but be associated with longer carbon payback times (Fig. 3d). The bioplastic target in Thailand may entail net GHG savings and the shortest carbon payback times, but still cause the loss of natural ecosystems within the country, with other potential environmental impacts such as biodiversity loss. Similarly, the metrics show that promoting bio-based production in China, and especially in the EU and US (based on current technologies) poses the risk of agricultural expansion and deforestation leakage in other countries; while other spillovers may arise in terms of fossil fuel extraction and GDP loss. Hence, it is recommended to assess additional metrics on leakage effects to check if potential GHG benefits of a policy come at the cost of sustainability in other regions. Other impacts besides deforestation and GHG emissions should ideally be considered, especially those typically associated with agricultural production, such as water depletion, acidification or eutrophication (Humpenöder et al., 2018; Ögmundarson et al., 2020). This may however require interdisciplinary collaboration to combine global and macro-economic with more regionalized approaches, with the associated challenges.

Global CGE models prove to be a powerful tool for quantifying land use impacts and spillovers of large-scale interventions, due to their ability to capture price-mediated supply and demand responses across markets and regions; as well as interlinkages between agricultural expansion, intensification and underlying yield adjustments. Nevertheless, CGE models also show limitations for comprehensively assessing and monitoring the sustainability of the bioeconomy, mainly because: a) key and emerging bio-based sectors are normally underrepresented; b) biophysical extensions are under development and mostly focus on land use, GHG and other emissions to air; c) sustainability outcomes are subject to modelling assumptions and parameter variability (see Table 1). As for the first issue, the tool used in this analysis, CGEBox, offers flexibility to disaggregate additional sectors from those in the original GTAP database, based on relative output shares. The problem with emerging sectors such as bioplastics or biochemicals is that these are normally strategic and data is confidential, which hampers a systematic disaggregation of these sectors on a global scale. It is important to note that the GTAP 10 database (Aguiar et al. 2019) already includes "rubber and plastic products" as a single sector, which could facilitate further assessments. However, the GTAP-AEZ extension (with consistent land use data) was not yet integrated with the GTAP 10 database by the time this study was carried out, preventing its application.

CGEBox also implements the Food and Agriculture Biomass Input-Output (FABIO) model (Bruckner et al., 2019) to disaggregate crops that are not explicitly represented as GTAP sectors but are relevant for the bioeconomy, such as maize, wheat, or soybean. Although this approach helps increasing the level of sectoral detail in the database in a straightforward manner, it also poses risks of inaccuracies relative to bottom-up data collection. Another limitation of CGE models arises from the fact that product and input flows are expressed in monetary units, which hinders the quantification of impacts from production and consumption on the biophysical environment. Efforts are underway to improve biophysical extensions and estimate other environmental impacts in CGE frameworks (Haqiqi et al., 2016; Sartori et al., 2019). As for socioeconomic indicators, CGE models mainly provide estimates on real GDP, though other indicators are desirable to capture social impacts from policies and technologies affecting land use (D'Amato et al., 2017; Hickel 2020; Mattila et al., 2018).

CGE models, same as any other modelling tool, come with assumptions and data collection challenges, which translates into uncertainty in model outcomes, e.g. iLUC factors (Daioglou et al., 2020; Malins et al., 2020). Sensitivity and uncertainty analyses are thus recommended to enhance the robustness and transparency of CGE-based results. CGEBox allows multiple scenarios to be simulated by changing as many model parameters as desired, in order to obtain probability distributions of deterministic values for key variables (see Fig. 1). This can be understood as an analysis of the epistemic uncertainty, although other techniques could alternatively be applied, such as Monte Carlo analysis (Plevin et al., 2010;2015). The uncertainty analysis presented here shows that a lower elasticity of substitution between bio- and fossil-based plastics (ESUBST) yields greater economic and environmental spillovers (Escobar et al., 2018). An inelastic supply of fossil fuels (ESUPP) yields the fewest side effects in terms of decrease in sectors' output and associated real GDP loss. It must be noted that the elasticity of substitution between bio- and fossil-based alternatives should ideally be specific for the type of product, i.e. higher for drop-ins. The 1% bioplastic target generates outliers to a greater extent than the other two, which underlines the importance of assessing relevant shocks in macro-economic terms (especially if emerging sectors are involved). Other parameters that need further scrutiny are the land supply elasticities to land rents in the extended GTAP-AEZ module, which are being refined as work-in-progress, based on econometric analysis. Another choice that is often controversial is the time period for straight-line amortization of iLUC emissions, which is chosen arbitrarily and can translate into big variations in iLUC factors (Plevin et al., 2010). This uncertainty in iLUC factors has often been used as a basis for questioning their suitability to inform policy-making, specifically in the area of biofuels (Daioglou et al., 2020; Finkbeiner 2014). However, the usefulness of these metrics lies in their ability to identify unwanted negative effects, rather than quantifying them accurately (Searchinger et al., 2015). The proposed metrics can thus provide valuable information to identify where complementary policies may be needed, e.g. to prevent deforestation leakage.

In spite of the uncertainty, what seems clear is that considering iLUC significantly increases both land and carbon footprints of bioplastics relative to those estimated under traditional LCA approaches. For instance, IEA (2020) quantifies a land use intensity of 0.35 ha per tonne of bioplastic produced in the EU, whereas the average land footprint of EU bioplastics is here estimated at 1.7, 3.0 and 3.9 ha t^{-1}, for increasing levels of market penetration (1%, 5% and 10%, respectively). Similarly, IEA (2020) estimates that each tonne of PLA or PHA could save around 3 t CO_2-eq. if replacing 20% of the EU plastic market with bioplastics; or Spierling et al., (2018) consider an emission factor of -1.85 t CO_2-eq. t^{-1} for PHA/PHB. Under the approach applied, average emission factors are here calculated at 1.00 and 6.62 t CO_2-eq. per additional tonne of bioplastics produced in the US and China, respectively (consisting of PLA and PHA/PHB); while the average emission factor of EU bioplastics production (mostly TPS) is estimated at 10.41 t CO_2-eq. t^{-1}. Emissions from iLUC outweigh overall GHG savings from fossil substitution and result in net GHG emissions per tonne of bioplastic; except for PBS produced in Thailand. This seems to be the only country where promoting bioplastic production from sugarcane and cassava by means of production subsidies could be a cost-effective strategy to reduce global GHG emissions in the short-term, i.e. after 18.6 years, with average annual abatement costs above 1,350 US\$ t^{-1} CO_2-eq. (see Fig. 3e). These metrics are however expected to increase as the bioplastic market expands in Thailand; requiring larger and potentially carbon-rich land areas converted to agriculture, similar as observed for Brazil. It must be borne in mind that the results from this analysis exclude other important GHG sources along the bioplastic life cycle, namely disposal, while neglecting other environmental impacts (Pawelzik et al., 2013; Weiss et al., 2012). Non-food-based bio-products, e.g. from perennial plants or residues, could alleviate competition for land between traditional and more advanced uses, hence mitigating iLUC effects (Moretti et al., 2020). Nonetheless, it may still take a few years to develop cost-effective routes to produce the full spectrum of chemicals based on these technologies (Brodin et al., 2017).

Besides feedstock diversification, other technological improvements could help reduce GHG emissions along the bioplastics supply chain, such as improving biomass productivity and conversion efficiencies (e.g. with new microbial strains/enzymes), optimising transportation logistics, or implementing cascading uses (e.g. in biorefineries) (Escobar and Laibach, 2021). However, in the last decades, technological development has mostly focused on enhancing technical functionalities of bioplastics (Philp et al., 2013). More recently, the chemical industry has been putting efforts into developing biopolymers with a higher performance and value (Babu et al., 2013). The market share of biodegradable bioplastics with enhanced mechanical properties (e.g. PHAs, PLA) is currently on the rise, mainly for packaging uses (Dietrich et al., 2017). Recyclability and composability of plastics can translate into economic and environmental benefits, e.g. in terms of both smaller carbon and material footprints (OECD 2013). However, actual recyclability depends on the availability of adequate collection and management systems. This is why drop-in products such as bio-PE and bio-PET still offer advantages at end-of-life, as these enter conventional waste streams. For instance, recycling PET is usually better than either composting or biodegrading PLA in landfills, due to significant methane releases (Krause and Townsend 2016; Ögmundarson et al., 2020). Indeed, end-of-life options are decisive in determining the environmental performance of bioplastics from cradle-to-grave, but depend largely on the geographical and political context (Changwichan et al., 2018; Papong et al., 2014; Zheng and Suh 2019). While mechanical recycling is usually the preferred option in both environmental and economic terms, it is not available for PLA in many countries (Changwichan et al., 2018; Ögmundarson et al., 2020). In this sense, durability of plastics and bioplastics can contribute to GHG mitigation if adequate technologies for material recycling or incineration with energy recovery are put in place (OECD 2013). Therefore, a greater integration and coordination between chemical and waste treatment sectors is crucial to simultaneously reduce waste, mitigate climate change and environmental degradation, and enhance the long-term sustainability of the plastics industry.

5. Conclusions

This study applies an integrated CGE framework (Britz and van der Mensbrugghe 2018) based on the GTAP model and extensions to derive quantitative indicators on the sustainability of crop-based bioplastics production in five major producing regions (Brazil, China, the EU, US and Thailand). The approach firstly requires disaggregating bioplastics and conventional plastics from the rest of chemicals, treating them as imperfect substitutes in consumption. The framework also modifies the GTAP-AEZ extension to introduce the possibility of expanding managed land uses at the expense of natural vegetation from a region-specific land buffer; in order to estimate market-mediated iLUC. Then, the approach consists of simulating bioplastic production targets in each region separately by means of production subsidies, following the various examples on biofuel mandates. Each target is defined as a share of the total plastics market to be replaced with bioplastics. This triggers different market-mediated responses depending on the region of study, the size of both its fossil-based plastic and bioplastic sectors, the underlying feedstock mix and trade relationships. The targets increase demand for starch or sugar crops, with the subsequent adjustments in crop prices and land rents, which ultimately translate into iLUC and GHG emissions on a global scale. Various metrics are proposed to interpret these outcomes and compare the sustainability risks of producing bioplastics in the regions considered, based on current technologies. To estimate the uncertainty in the results, different scenarios are assessed, representing increasing levels of market penetration of bioplastics; as well as different levels of substitutability between bioplastics and conventional plastics and different price elasticities of supply of fossil fuels. In total, 36 scenarios are simulated per region, allowing probability distributions to be obtained for each of the indicators proposed. These include land and carbon footprints, CO_2-eq. emission factors, carbon payback times and abatement costs; as well as additional metrics on leakage effects in terms of cropland area expansion, deforestation, fossil fuel consumption or real GDP loss.

The results show that the sustainability performance of bioplastics varies across regions and scenarios, while trade-offs arise among the metrics proposed. None of the regions has clear sustainability comparative advantages in bioplastic production, besides Thailand. However, this is related to the very small production of both fossil- and bio-based plastics in the base year as compared to the other regions, which translates into minor market-mediated effects. On the contrary, increased bioplastics production in China is associated with the largest land footprints, due to the relatively greater increase in bioplastics production needed to meet the target. Bioplastics produced in the EU have on average the highest CO_2-eq. emission intensity, when including emissions from iLUC. This reflects the relatively large share of imported feedstock in EU bioplastics production, which causes significant price-mediated responses across agri-food markets. Emissions from iLUC outweigh potential GHG savings from fossil fuel substitution in the regions considered, except for Thailand. Promoting bioplastics production by means of production subsidies is not an effective strategy to mitigate climate change, since it results in long carbon payback times and GHG emission increases in the short- and even long-term.

The longest carbon payback times are, on average, estimated for the bioplastic targets in the EU and Brazil, both above 170 years. While in Brazil this is mostly due to domestic losses of carbon-rich ecosystems, an increased production of bioplastics in the EU causes the greatest carbon losses outside the region. This highlights the need to consider additional metrics in order to identify where complementary policies may be needed to prevent spillovers. Other impacts besides deforestation and GHG emissions should also be considered to capture trade-offs within the Water-Food-Energy nexus, such as water depletion, acidification or eutrophication; as well as additional socioeconomic and social indicators. In this sense, CGE frameworks could greatly benefit from interdisciplinary collaboration to combine global and macro-economic with more regionalized approaches for the development of biophysical modules. In spite of these limitations, CGE analysis provides a powerful scientific framework for systematic sustainability assessment, since it ensures robustness in analytical steps, estimates multiple quantitative indicators simultaneously and allows for uncertainty analysis through 'what-if' scenario design.

Credit author statement

Neus Escobar: Conceptualization; Formal analysis; Methodology; Validation; Visualization; Writing - original draft

Wolfgang Britz: Conceptualization; Methodology; Software; Supervision; Validation; Writing - review & editing

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2020.105345.

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