Biofuel Research Journal 34 (2022) 1608-1616

Journal homepage: www.biofueljournal.com

Original Research Paper

On quantifying sources of uncertainty in the carbon footprint of biofuels: crop/feedstock, LCA modelling approach, land-use change, and GHG metrics

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HIGHLIGHTS

- Uncertainty in the carbon footprints of biofuels is large.
- Uncertainty comes from crop used, LUC and LCA modelling, but not GHG metrics.
- Uncertain parameters should be dealt with consistently with the goal and scope.
- Results should be interpreted in light of the methodological choices made.
- Sensitivity analysis is recommended.

GRAPHICAL ABSTRACT

ARTICLE INFO

Article history:
Received 7 February 2022
Received in revised form 18 March 2022
Accepted 19 March 2022
Published 1 June 2022

Keywords:
indirect Land-Use Change (iLUC)
Climate change mitigation
Life cycle assessment
Carbon footprint
Biofuels
Uncertainty

ABSTRACT

Biofuel systems may represent a promising strategy to combat climate change by replacing fossil fuels in electricity generation and transportation. First-generation biofuels from sugar and starch crops for ethanol (a gasoline substitute) and from oilseed crops for biodiesel (a petroleum diesel substitute) have come under increasing levels of scrutiny due to the uncertainty associated with the estimation of climate change impacts of biofuels, such as due to indirect effects on land use. This analysis estimates the magnitude of some uncertainty sources: i) crop/feedstock, ii) life cycle assessment (LCA) modelling approach, iii) land-use change (LUC), and iv) greenhouse gas (GHG) metrics. The metrics used for characterising the different GHGs (global warming potential-GWP and global temperature change potential-GTP at different time horizons) appeared not to play a significant role in explaining the variance in the carbon footprint of biofuels, as opposed to the crop/feedstock used, the inclusion/exclusion of LUC considerations, and the LCA modelling approach ($p<0.001$). The estimated climate footprint of biofuels is dependent on the latter three parameters and, thus, is context-specific. It is recommended that these parameters be dealt with in a manner consistent with the goal and scope of the study. In particular, it is essential to interpret the results of the carbon footprint of biofuel systems in light of the choices made in each of these sources of uncertainty, and sensitivity analysis is recommended to overcome their influence on the result.

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Contents

Abbreviations

CF	Carbon footprint
char	LCA characterization model
crop	Crop or feedstock
dLUC	direct Land Use Change
FAME	Fatty acid methyl ester
FAO	Food and Agriculture Organization of the United Nations
GHG	Greenhouse gas
GTP	Global temperature change potential
GWP	Global warming potential
HVO	Hydrotreated vegetable oil
iLUC	indirect Land Use Change
LCA	Life Cycle Assessment
LUC	Land-Use Change
PVO	Pure vegetable oil
luc	Inclusion/exclusion of dLUC or iLUC
mod	LCA modelling approach (ALCA and CLCA)
η^2	Eta-squared, a measure of effect size used in ANOVA

1. Introduction

The urgent need for replacing fossil fuels to mitigate climate change has stimulated the development of policies promoting biofuels. Policies supporting transport biofuels have been implemented over the last two decades, but with little critical appraisal of the context in which these systems deliver a net reduction in greenhouse gas (GHG) emissions (Searchinger et al., 2008; Plevin et al., 2014). Given the wide range of biofuel systems available in terms of crops/feedstocks (e.g., sugar, starch, vegetable oil and organic by-products) and conversion processes (e.g., esterification, distillation), there is an associated large variability in the carbon footprint of those systems (Malça and Freire, 2010; Pfister and Scherer, 2015).

It is intuitive that products resulting from bio-based systems will be more climate-friendly than those from their fossil counterparts (Weiss et al., 2012). The rationale for the early view that biofuels were carbon neutral was that the carbon emitted upon combustion had been sequestered from the atmosphere in the first place, as crops photosynthesise and grow, giving no net CO_2 emissions. However, once the whole life cycle is taken into account, including agrochemical inputs (e.g., N fertiliser, the production of which is a GHG-intensive process (Wood and Cowie, 2004), changes in the carbon stock in the land where the crops are grown (which may be positive or negative, depending on the previous land use), indirect land-use change (iLUC), as well as albedo effects, it becomes evident that bioenergy's impact on climate change is not neutral (see, e.g., Searchinger et al., 2008; Cherubini et al., 2009, Johnson, 2009; Haberl et al., 2012; Zanchi et al., 2012; Wiloso et al., 2016), highlighting the need to support only the systems that can result in real climate change mitigation.

The application of environmental systems analysis tools, such as life cycle assessment (LCA), has elucidated that the assumed climate benefit of biofuels is not always realised (Brandão et al., 2021), not least because indirect effects are usually not accounted for, such as iLUC (Searchinger et al., 2008). Clearly, biofuel systems need to be analysed quantitatively and comprehensively before robust claims can be made about their relative environmental superiority.

The need to assess systems comprehensively along their supply chain led to the recognition that LCA is the appropriate decision-support tool for assessing the impacts of biofuel systems (EU, 2009). LCA comprehensively compares alternative systems with the same functionality, providing a proper basis to inform policy to support a transition towards more sustainable production and consumption. LCA helps identify trade-offs between alternatives and highlights risks of shifting burdens between impacts, life cycle stages, generations, and countries (Brandão, 2020).

LCA can elucidate climate change effects of biofuel systems and thereby aid in comparing energy systems and in identifying those that meet the targets that policymakers have set. LCA has been used to support policy development and implementation, e.g., EU RED (EU, 2009). However, despite its standardisation (ISO 2006a and b), the application of LCA has resulted in quantified benefits of biofuel systems that vary widely and depend on methodological choices (Cherubini and Stromman 2011; Ahgren et al., 2015; Brandão, 2020). Unresolved methodological issues in applying LCA to biofuel systems hinder the generation of robust results for supporting policy decisions (McManus et al., 2015; Agostini et al., 2020).

There are several factors that explain the variability of carbon footprint estimates of biofuel systems. Agricultural and other bio-based systems are naturally variable, given their susceptibility to local climate vagaries and other agroecological factors, such as soil type. Furthermore, uncertainty in footprint estimates may be due to management factors (crop/feedstock type, inputs, agronomy), as well as processing technologies and scale. Altogether, these reflect known variations between biofuel systems. In addition, variability comes from methodological aspects, such as the impact assessment method (Brandão et al., 2019), which reflect methodological choices made by the practitioners. In this article, we consider the combined effects of variation in results due to differences in feedstock and methodological choices as sources of variability and/or uncertainty.

Methodological choices relate to the LCA phases of the study: (i) the goal and scope definition, including the intended application and system boundary, the modelling approach (attributional or consequential) and treatment of land-use change; (ii) the life cycle inventory (LCI) analysis, including the data type (e.g., marginal or average) and sources, where data are collected, and inputs and outputs are quantified, which should be consistent with (i); (iii) the life cycle impact assessment (LCIA) method to be adopted for characterising emissions of GHGs, and (iv) interpretation, including assumptions related to the climate-change-mitigation potential of the assessed biofuels. The variation in applied methodologies reflects differences in purpose between studies and arises from unresolved issues surrounding the LCA of bio-based systems in general and biofuel systems in particular (Wiloso et al., 2012; Brandao et al., 2021). Indeed, the freedom with which LCA practitioners have applied LCA to energy systems, not

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always compliant with the ISO 14040/44 standards (ISO, 2006a and b), has resulted in wide variation in the reported values for published GHG emissions (see, e.g., Chum et al., 2011; Sathaye et al., 2011; Garcia et al., 2020). In the case of biodiesel from microalgae, the results can be highly variable (see Garcia et al., 2020), but high variability also applies to other feedstocks and other biofuels (Brandão et al., 2021).

Uncertainty in LCA has been subject to several analyses, mainly when LCA is used for comparative purposes (see, e.g., Groen and Heijungs, 2017; Mendoza Beltran et al., 2018; Igos et al., 2019; Cucurachi et al., 2021; Heijungs, 2021). In terms of the carbon footprint of biofuels, several sources of uncertainty make the estimation of impacts extremely variable, such as i) crop/feedstock, ii) land-use change, iii) modelling approach, and iv) GHG metrics.

1.1. Crop/feedstock

Crops can be converted to biofuels through several processes. Sugar and starch crops can be fermented to produce ethanol, while oilseed crops produce pure vegetable oil (PVO) that can be esterified to biodiesel (fatty acid methyl ester-FAME) or hydrotreated to produce hydrotreated vegetable oil (HVO), also known as renewable diesel. For ethanol, corn is the common feedstock in the USA, while sugarcane is used in subtropical regions such as Brazil, and wheat and barley are used in Europe. Oilseed crops are also geographically-specific: while oil palm is grown in South-East Asia, e.g., Indonesia and Malaysia, oilseed rape is produced in Europe and soybean in South America. The different crops have different agronomic requirements and product properties, thus, feature different production and processing systems.

1.2. Modelling approach

In the first phase of LCA, the goal and scope definition, a decision is made on how the biofuel system is represented. The particular modelling approach for calculating life cycle GHG emissions relies on a specific delimitation of the system boundary, whereby by-products are excluded *via* substitution or allocation.

When representing the product system under assessment, mainly two modelling approaches are followed: attributional LCA (ALCA) and consequential LCA (CLCA). According to the Shonan LCA database guidance principles, the two LCA modelling approaches are defined as follows (Sonnemann and Vigon, 2011):

- Attributional approach: A system modelling approach in which inputs and outputs are attributed to the functional unit of a product system by linking and/or partitioning the unit processes of the system according to a normative rule.
- Consequential approach: A system modelling approach in which activities in a product system are linked so that activities are included in the product system to the extent that they are expected to change as a consequence of a change in demand for the functional unit.

The two approaches answer different questions: whilst ALCA attributes a share of the global environmental burden to a product or activity, a CLCA quantifies the consequences that an increase in supply or demand for a particular product is likely to have on the environment in a given context. It has been argued that ALCA cannot support decision-making, while CLCA can, as ALCA does not attempt to estimate the consequences of decisions (Brandão, 2014); some authors even argue that ALCA is unequivocally misleading in guiding policy, e.g., climate policy (Plevin et al., 2014).

In practice, the main differences between the two approaches relate to: i) the data adopted (average for ALCA and marginal for CLCA; e.g., for modelling the input of electricity supply mix or land-use reference system), and ii) the manner by which co-production is handled. ALCA commonly allocates environmental burdens among co-products according to energy content or economic value, while CLCA typically follows a substitution approach whereby the determining product (e.g., wheat ethanol) is credited with the avoided burdens that the use of the by-product (e.g., energy recovery from wheat straw) incurs *via* displacing a marginal product yielding the same function as the by-product (e.g., 1 MJ of heat from straw displacing an equivalent amount of heat from natural gas). More information on these two modelling approaches can be found in Weidema (2003), Brandão et al. (2014), Brandão et al. (2017), and Ekvall (2019).

Regardless of the support that either modelling approach may have in the LCA community, which remains a divisive issue, it is undeniable that applying the two approaches results in highly disparate outcomes (Brandão et al., 2021). For example, when modelling palm oil, Schmidt and de Rosa (2020) reported considerably variable results, but the variability found depended on the impact category under consideration (from -63% for respiratory inorganics to +730% for mineral extraction when comparing attributional to consequential results). It has also been argued that beyond this dichotomy between ALCA and CLCA, other forms of LCA exist and that the goal should be to develop useful models (Suh and Yang 2014).

In addition to the two LCA modelling approaches discussed above, hybrid approaches exist that use both substitution and energy allocation, like that described in RED (EU, 2009). The RED (EU, 2009), now superseded by Directive (EU) 2018/2001 (EU, 2018), stipulated that biofuels should abide by certain criteria and targets, such as having a carbon footprint 35% lower than fossil fuels. In order to calculate GHG savings, RED follows a life cycle approach to estimate the climate change impacts of biofuel systems - see Annex V of the RED (EU, 2009) – which is used to calculate the default values for various biofuel systems, to support identification of biofuel systems that met the criterion of 35% GHG emission savings relative to the fossil-fuel comparator of 83.8 gCO_2-eq., and it showed that some pathways did not meet the threshold of minimum GHG savings, such as wheat ethanol, soybean biodiesel, and palm oil biodiesel (saving 16%, 31% and 19%, respectively; EU, 2009).

1.3. Land-use change (LUC)

LUC refers to conversion between land uses (e.g., forest, grassland, cropland), generating carbon fluxes between terrestrial ecosystems and the atmosphere. The use of land for biofuel crops causes CO_2 emissions if the carbon stock of the biofuel crop is lower than the carbon stock of the reference land use. If the land used for annual biofuel crops has existed as cropland for a “reasonable” time – usually considered 20 yr – then no emissions for LUC are ascribed to the biofuel as there were no significant biogenic carbon emissions over the previous two decades. However, if grassland or forest is used for biofuel crops, the magnitude of emissions would be considerably higher and should be ascribed to the activity responsible for LUC, i.e., biofuel, in this case. Replacing annual crops with perennial biofuel crops can lead to carbon dioxide removal.

The particular land use adopted as a reference may depend on whether the modelling approach is attributional or consequential and has a decisive contribution to the outcome of the analysis (Soimakallio et al., 2015; Koponen et al., 2018; Donke et al., 2020). In addition, a more complex concern exists for indirect LUC (iLUC). As opposed to direct LUC (dLUC), iLUC refers to changes in land use that take place indirectly to compensate for the diversion of crops from, e.g., food and feed purposes, into biofuel production. For example, the diversion of corn from animal feed to ethanol in the USA could lead to the expansion of soybean on pastures in South America to meet feed demand, indirectly causing forests to be cleared for grazing (Brandão, 2008; Song et al., 2021).

Concerns over the indirect implications for climate change of using land for biofuels were expressed in the European Commission (2015) iLUC “Directive” (2015/1513) (European Commission, 2015), where it was recognised that the emissions associated with some biofuels receiving EU subsidies could exceed the fossil fuels that they replaced when indirect effects were included. A subsequent review of iLUC factors by Valin et al. (2015) and Woltjer et al. (2017) illustrated the high variability of iLUC factors as determined by a range of models, including partial and general economic-equilibrium models, and questioned whether models were suitable for determining factors to quantify an effect that cannot be directly observed or measured (Munoz et al., 2015). It is widely acknowledged that estimating iLUC emissions is highly challenging.

1.4. GHG metrics

As discussed above, biofuel systems are not carbon neutral. However, the biogenic part of the carbon emission has been considered neutral in many LCA studies for the reasons mentioned above. Provided carbon is

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emitted as CO_2 and not as CH_4, biogenic carbon emissions from combustion of biofuels could indeed be considered neutral and disregarded, as long as allocation between co-products is treated consistently, i.e., allocated on the basis of their carbon content (see Luo et al., 2009). This assumption is valid as long as there is no substantial divergence between the timing of uptake and emissions, such as in the case of annual crops, and no dLUC emissions, such as due to a decline in soil carbon stocks.

In the case of perennial crops, there is a rationale for differentiating emissions based on their timing, even if overall biogenic emissions are balanced by an equivalent amount of carbon sequestered as biofuel feedstocks grow. The reason is that one may legitimately want to credit systems that keep carbon out of the atmosphere for longer periods of time (e.g., while an annual crop removes atmospheric carbon for one year, a forest plantation can remove carbon for as much as 100 yr). This has justified the emergence of several methods that account for the timing of emissions. A recent comparison of 15 methods by Brandão et al. (2019) found wide variation between methods, particularly where biofuel crops replace forest, such that, depending on the method applied, a biofuel may appear better or worse than the fossil fuel it replaces.

In addition to the aspect of time, different GHG characterisation models reflect different cause-effect mechanisms. The most common LCIA characterisation models are those from which Global Warming Potentials (GWPs) and Global Temperature change Potential (GTPs) are derived. While the former reflects the cumulative radiative forcing over a period (e.g., 20 and 100 yr), the latter reflects temperature changes at the end of the period (Cherubini et al., 2016; Levasseur et al., 2016; Jolliet et al., 2018). These GHG metrics also vary in the weighting they attribute to short-lived climate forcers such as methane relative to CO_2 (Jolliet et al., 2018).

The aim of this study is to identify the sources of uncertainty that make the estimation of the carbon footprint of biofuels extremely variable. With reference to a range of biofuel systems, this paper quantifies the magnitude of the uncertainty associated with each of the main sources: i) crop/feedstock, ii) land-use change, iii) modelling approach and iv) GHG metrics, which is currently lacking in the existing scientific literature on the topic. The goal is that this study will contribute to improved assessments with reduced uncertainty and greater consistency that provide more accurate, comparable data to inform decision-making.

2. Research Methodology

The magnitude of the different sources of uncertainty associated with modelling the carbon footprint of biofuels was quantified: i) crop/feedstock, ii) LUC considerations, iii) LCA modelling approach, and iv) LCIA characterisation model for GHG emissions. The inventory data and modelling for the 20 biofuel pathways are based on Brandão et al. (2021), extended in this work to include two LCIA methods (over two periods) and visualisations of variability.

Specifically, estimates reflect the inclusion or exclusion of dLUC and iLUC, as well as 2 different characterisation models (GWP and GTP) over two time frames (20 and 100 yr). In total, each pathway's different permutations of the modelling approach, LUC considerations and LCIA characterisation models resulted in 28 estimates, giving a total of 560 data points.

2.1. Crop/feedstock

The GHG emissions (i.e., CO_2, CH_4, and N_2O) associated with the life cycle of 20 biofuel production pathways from 10 crops/feedstocks (including supply chain data: country- and crop-specific yields, fertilizer, and fuel use, etc.) were modelled, as described in Brandão et al. (2021):

- ethanol (7 pathways): corn from the USA, sugar beet from France and Germany, sugar cane from Brazil, and wheat from France and Germany (4);
- FAME (6 pathways): palm oil from Malaysia and Indonesia (2), rapeseed oil from France and Germany, sunflower oil from the Ukraine, soybean oil from the USA and Argentina and waste oil;
- HVO (4 pathways): palm oil from Malaysia and Indonesia (2), rapeseed oil from France and Germany, and sunflower from Ukraine;
- PVO (1 pathway): rapeseed oil from France and Germany; and
- biogas (2 pathways): wet and dry manure from dairy cows in France and Germany.

2.2. Modelling approach

Each of the biofuel pathways was modelled in three different ways reflecting the different modelling approaches: ALCA, CLCA, and EU-RED (see *Section 1.2* for a description of the different modelling approaches). While the ALCA and CLCA approaches respectively applied energy allocation and substitution consistently, the EC-RED approach applied a mixture of energy allocation and substitution.

2.3. Land-use change (LUC)

Estimating dLUC and iLUC emissions is challenging (see *Section 1.3*). For dLUC, values from the study by Brandão et al. (2021) were used, which takes into account how much the land area devoted to a specific crop changed over the preceding 20 yr. IPCC data were used, as well as FAO data on cropland expansion in specific countries where the feedstocks are grown and compared with the contraction of other land uses, such as grassland and forest, to estimate LUC emissions. LUC emissions were calculated from the average share of production that came from cropland expansion over that period. Reference land use (e.g., arable land, grassland, and forest) and associated carbon stock were determined as a weighted average of those land uses that contracted over the same period. This was applied across all modelling approaches.

The need for standardisation of iLUC factors for policy implementation led the EU (2015) to base their adopted default values on a general-equilibrium model *Modeling International Relationships in Applied General Equilibrium* (MIRAGE), developed by the International Food Policy Research Institute (IFPRI): 12 (8-16) g CO_2-eq. MJ^{-1} for cereals and other starch-rich crops, 13 (4-17) g CO_2-eq. MJ^{-1} for sugar crops, and 55 (33-66) g CO_2-eq. MJ^{-1} for vegetable oil crops. These iLUC values were adopted in the RED approach. For the ALCA and CLCA approaches, the framework developed by Schmidt et al. (2015) was adopted, whereby a single emission factor was estimated for iLUC under each LCA modelling approach for agricultural land used in the foreground biofuel system, as well as in the background feed and vegetable oil systems in the case of CLCA. These factors were estimated based on the following biophysical step procedure: i) the land requirement per MJ of biofuel was estimated, taking into account the location where the feedstocks are grown; ii) the potential net primary production (NPP_0) of those locations was estimated; iii) the productivity factor was estimated by dividing the biofuel crop yield by the global average productivity of arable land, that is, 6.11 t $C\cdot ha^{-1}\cdot yr^{-1}$; iv) the actual occupied area (ha·yr) was converted into units of productivity-weighted hectare-years (pw ha·yr); v) GHG emissions were estimated for both attributional and consequential approaches by multiplying the iLUC GHG emissions per pw ha·yr for arable land reported by Schmidt et al. (2015) of 1.260 and 0.042 t $CO_2\cdot pw\ ha^{-1}\cdot yr^{-1}$ for CLCA and ALCA, respectively, by the total pw ha·yr of each biofuel pathway. The calculated result was included in the inventories.

2.4. GHG metrics

GWP and GTP over/at both 20 and 100 yr from IPCC's fifth assessment report (Myhre et al., 2013) were applied as the LCIA characterisation model to estimate climate change effects. This yielded four results per combination of crop/feedstock, modelling approach and LUC/iLUC approach. The timing of emissions/removals was not differentiated.

2.5. Statistical analysis

Analysis of variance (ANOVA) was applied to estimate the contribution of the four uncertainty sources: i) crop/feedstock, ii) dLUC/iLUC considerations, iii) LCA modelling approach, and iv) LCIA characterisation model for GHG emissions. A 4-way ANOVA was performed with the above four parameters, without interaction, using the model which is symbolically written as **Equation 1**:

$$CF_{c,luc,mod,char} = \mu_{overall} + \alpha_{crop} + \alpha_{luc} + \alpha_{mod} + \alpha_{char} + \varepsilon \qquad \text{Eq. 1}$$

where $CF_{crop,luc,mod,char}$ is the carbon footprint of a biofuel in $gCO_2eq.MJ^{-1}$ with certain *crop* (crop/feedstock) characteristics, *luc* (treatment of land-use change) choice, *mod* (modelling approach), and *char* (characterisation model). The term α indicates the mean effect in each group, $\mu_{overall}$ the mean of all carbon footprints, and ε is the residual term of the statistical model. This model assumes that the effects of the four parameters ($crop$, luc, mod, and $char$) are independent. The null hypothesis is that the mean effects α of all four terms is zero.

3. Results and Discussion

Figure 1 shows the variation of data points, which is particularly high for sugar cane ethanol, palm oil biodiesel (both FAME and HVO, with and without methane capture), and soybean oil biodiesel. The reader is referred to Brandão et al. (2021) to discuss the factors driving differences between the feedstocks.

Figure 2 shows the variability of results in each of the four dimensions. In terms of crop/feedstock, results are particularly variable for palm oil biodiesel (with and without CH_4 capture), soybean oil biodiesel, and sugar cane ethanol. In terms of LUC, results are variable when both dLUC and iLUC are included, but also when only dLUC is included. In terms of the modelling approach, CLCA shows the most considerable variability. Finally, in the last dimension, choice of the characterisation model, results were similar.

The ANOVA table (**Table 1**) shows that the factors *crop* (crop/feedstock used), *luc* (LUC considerations), and *mod* (modelling approach) provide a highly significant explanatory effect, the first factor explaining more than 30% of the variance. Factor *char* (GHG characterisation factors) is not a significant explanatory variable. The η^2 shows that these four factors explain 40.75% of the variation in *CF* results.

Table 1. 4-way ANOVA table.

Factor[1]	Df	Sum Sq	Mean Sq	F value	Pr (>F)		Partial $\eta 2$
crop	14	2,175,257	155,376	22.101	$<2 * 10^{-16}$	***[2]	0.366
mod	2	519,130	259,565	36.921	$9.47 * 10^{-16}$	**	0.086
luc	3	133,976	44,659	6.352	0.000309	***	0.034
har	3	42,648	14,216	2.022	0.109783		0.011
Residuals	537	3,775,303	7,030	-	-		-

[1] Abbreviations: *crop* (crop/feedstock used), *luc* (LUC considerations), *mod* (modelling approach), and *char* (GHG characterisation factors). Df: degrees of freedom and Pr: Probability.
[2] Significance codes: '***' = p<0.001

One of the assumptions of ANOVA is that the residuals are normally distributed. This is not the case, as can be seen in a QQ-plot (**Fig. 3**). However, this is not concerning because ANOVA is reasonably robust against non-normality (Ott and Longnecker, 2015), the sample size is fairly large, and the effects are clear; it is believed that the conclusion is justified: the factors crop/feedstock, LUC and model, have a highly significant influence on the resulting carbon footprint, while the characterisation model is insignificant for these biofuel pathways.

Despite the existence of previous research on the uncertainty in life cycle assessment, focusing on that associated with biofuel systems (e.g., Pfister and Scherer, 2015; Lo Piano and Benini, 2022) or with the choice of modelling approach (e.g., Brandão et al., 2021; Schaubroeck et al., 2021; Bamber et al., 2020), or with handling co-production (e.g., Obydenkova et al., 2021) or choice of LCIA methods (e.g., Cherubini et al., 2018; Brandão et al., 2019), or with modelling LUC (e.g., De Rosa et al., 2018), and with which our results are compatible, the simultaneous consideration of crop/feedstock, LCA modelling approach, LUC and GHG metrics, and the

Fig. 1. Carbon footprint of ethanol, biodiesel (FAME), renewable diesel (HVO), and biogas produced from 20 different feedstocks estimated with the three modelling approaches (ALCA, CLCA, EC-RED), inclusion/exclusion of dLUC and iLUC considerations, four LCA characterisation models (GWP over 20 and 100 yr, and GTP after 20 and 100 yr). The legend read from top-down corresponds to the bars read from left to right.

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Fig. 2. Variability in the carbon footprint ($gCO_2eq.MJ^{-1}$), split by **(a)** 15 different crops/feedstocks (crop), **(b)** 3 different LCA modelling approaches (mod), **(c)** 4 different land-use change treatments (luc), and **(d)** four different LCIA characterisation models (char).

Fig. 3. QQ-plot of the residuals of the ANOVA model. The vertical axis shows the quantiles of the estimated residual, and the horizontal axis shows the theoretical quantiles for a standard normal distribution.

sensitivity of results to the modelling choices made in these four parameters, has not been subject to scrutiny in published literature.

4. Conclusions and future research directions

It was estimated how much each source of uncertainty contributes to the overall uncertainty in estimates of carbon footprint for 20 biofuel systems. These results were not expected *a priori*, and they suggest important strategies for analysing the benefits of biofuels. While it is concluded that LCIA characterisation models for GHG emissions play an insignificant role for these biofuel pathways (this would not necessarily be the case for other systems with a more significant share of methane or if the timing of emissions/removals was included), the modelling approach, the feedstock used, and the treatment of LUC all play a significant role in the variability of the carbon footprint of biofuels.

The crop-biofuel pathway affects results because pathways represent very different crop production systems in terms of their inputs and outputs, and processing technology varies between end-products (ethanol, biodiesel, biogas). The differences between crops also reflect their production location, as, e.g., carbon stocks and management intensity differ between Europe, South America, and South-East Asia, affecting the LUC emissions, among others.

The primary source of variability – e.g., in the most uncertain pathways (Palm oil FAME and HVO, with and without CH_4 capture, soybean oil FAME, and sugar cane ethanol) – is the inclusion or exclusion of both dLUC and iLUC. Treatment of LUC is particularly critical given i) the locations where these crops are grown: South-East Asia and South America (where they may be grown on recently-cleared forest land), and ii) the modelling approach due to the different treatment of co-products (and associated LUC implications). Biofuels made from temperate crops, such as corn, rapeseed, and wheat, are largely grown in regions cleared for agriculture hundreds of years ago, and no further deforestation occurs. The variability is relatively low when only iLUC is included because only one of the variants of the EC-RED approach considers iLUC and excludes dLUC and because the indirect emissions are assumed by crop type rather than calculated: similar or the same factors across ethanol (12 or 13g CO_2-eq. MJ^{-1}) and biodiesel feedstocks (55g CO_2-eq. MJ^{-1}), respectively, are used.

It is clear from the analysis that methodological choices regarding, for example, the modelling approach and the treatment of LUC do affect the results. This does not mean that these sources of uncertainty should be ignored, as ignoring uncertainty would not avoid uncertainty and could give misleading results (Weidema, 2009). Brandão et al. (2014) highlighted the distinction between precision and accuracy, arguing for the relative importance of the latter. Attempts at making the modelling of a system precise may lead to low accuracy and biased results, while aiming for accuracy may result in low precision but representative results. As has been recognised in policy, it is crucial that indirect effects, such as iLUC, be included in the assessment of biofuel systems, even if doing so may lead to low precision (i.e., high variability of estimates). As Tribus and El-Sayed (1982) better stated, “It is much more important to be able to survey the set of possible systems approximately than to examine the wrong system exactly. It is better to be approximately right than precisely wrong.” It would be unwise to support systems for their alleged climate change mitigation potential if, when taking indirect effects into account, these systems are likely to have the opposite effect.

The insignificant effect of GHG metrics in this study is because the modelled systems had a similarly tiny fraction of emissions as CH_4. In addition, GWP and GTP do not differentiate emissions with respect to their timing. It is emphasised that the result is particular to the biofuel systems assessed here, where most of the biofuels modelled are made from annual crops and assessed with LCIA methods that do not distinguish the timing of emissions. A more significant effect may be likely when studying systems where asynchrony between the timing of emissions and removals occurs, such as bioenergy systems from forestry if methods distinguishing the timing of emissions are adopted (see Brandão et al., 2019).

Parameters additional to the four studied here may also significantly influence the results. However, it is believed that this paper addresses the main sources of uncertainty.

Biofuel systems have come under increasing scrutiny due to the urgent need to replace fossil fuels in order to mitigate climate change. This paper has clarified the importance of choices related to key methodological issues in the carbon footprinting of biofuel systems and demonstrated the dependency of climate-change results on the crop modelled, inventory-modelling approach adopted, land-use reference system, indirect land-use change, the inclusion of biogenic carbon flows, and LCIA method applied for characterising GHGs.

LCA is the established framework to assess the climate effects of biofuel systems. However, the above methodological choices required when performing an LCA study significantly impact the results and their interpretation. Furthermore, these methodological choices are the topic of ongoing debate; there is no consensus amongst experts and, therefore, no clear, agreed guidance to practitioners. The inconsistent handling of these methodological choices has led to an inconclusive evidence base for the climate effects of biomass and biofuel systems, with the biofuel systems reported as both positive and negative relative to their fossil counterpart.

The carbon footprint of biofuel systems can help identify the systems that meet policy targets, such as those that show a relatively lower carbon footprint. However, this study makes clear that methodological choices do determine the results and that the delimitation of the system boundary derived from the modelling approach, which determines the extent to which indirect effects are included, is a significant source of uncertainty. It is crucial that the models produced do not misrepresent the system under analysis by placing relevant activities outside the system boundary, which would go against the whole rationale for adopting a life cycle approach: not shifting burdens nor incurring “leakage”. In particular, it is important to interpret the results of the carbon footprint of biofuel systems in light of the choices made in each of these sources of uncertainty, and a sensitivity analysis is recommended to overcome their influence on the result.

Despite their uncertainty, the relevance of LCA and carbon footprinting for policy support is growing (Sala et al., 2021). Nonetheless, the lack of scientific consensus on handling critical methodological choices makes clear the need for increasing harmonisation in LCA and carbon-footprinting practice in order to improve the robustness and reproducibility of the results generated. We encourage scientists and decision-makers to address this issue urgently so that actions aimed at climate-change mitigation can be identified and realised. In this vein, more research on the robustness of carbon-footprint estimates *via* LCA is an important gap to be filled.

Acknowledgements

The authors would like to thank Elias Azzi for his early contributions to the paper.

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Please cite this article as: Brandão M., Heijungs R., Cowie A.L. On quantifying sources of uncertainty in the carbon footprint of biofuels: crop/feedstock, LCA modelling approach, land-use change, and GHG metrics. Biofuel Research Journal 34 (2022) 1608-1616. DOI: 10.18331/BRJ2022.9.2.2