Biofuels induced land use change emissions: The role of implemented emissions factors in assessing terrestrial carbon fluxes

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25th Annual Conference on Global Economic Analysis
Accelerating Economic Transformation, Diversification and Job Creation
June 8-10, 2022: Virtual

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1. Introduction

Since the late 2000s, various efforts have been made to assess Induced Land Use Change (ILUC) emissions due to biofuel production and policy. To accomplish this task, regardless of the differences, the examined experiments followed a common approach consisting of two sequential steps: i) using an economic model to project land use changes by region for a given biofuel type and ii) implementing a set of Land Use Emission Factors (LUEFs) combined with some supporting assumptions to convert the projected land use changes to GHG emissions, usually measured in gCO_2e.

The existing literature has frequently noted that the estimated ILUC emissions values are uncertain (EPA, 2010; Plevin et al., 2010; Laborde, 2011; Taheripour and Tyner, 2013; CARB, 2014; Valin et al, 2015; Plevin et al., 2015; Zilberman, 2017; Chen et al., 2018; and many more). The variations in modeling assumptions and data, modeling structures, and implemented economic parameters are identified as the main sources of uncertainties in ILUC emissions values. However, only a few papers have studied uncertainties in LUEFs and their associated assumptions. Plevin et al. (2015) have made a sensitivity test using the GTAP-BIO model combined with the AEZ-EF emissions accounting model (Plevin et al., 2014) and concluded that the estimated ILUC emissions values are more sensitive with respect to the changes in economic parameters than the changes in emissions factors. However, in their sensitivity test, these authors ignored that the AEZ-EF model is not the only available source of LUEFs. Unlike this biased finding that only relied on the AEZ-

EF emissions accounting model, Taheripour and Tyner (2013) have used different sets of emissions factors in combination with the GTAP-BIO model results on land use changes and concluded that the estimated ILUC emissions values vary significantly with changes in the implemented emissions factors obtained from alternative sources.

In another practice, Chen et al. (2018) have mixed the GTAP-BIO results on land use changes for a few biodiesel pathways with the AEZ-EF and CCLUB emissions accounting frameworks[1]. They showed that the ILUC emissions values vary significantly with the implemented LUEFs used in these emissions accounting frameworks. In particular, they showed that the selected LUEFs for marginal cropland could largely alter the estimated ILUC emissions values. Besides these limited studies, the role of emissions factors in assessing ILUC emissions values has not been evaluated well.

This paper aims to fill this knowledge gap with two different but related research activities. The first research activity studies the available sources of information on vegetation and soil carbon data sets that have been used in developing LUEFs to understand their similarities and differences across various land types and ecological conditions. The second research activity mixes the estimated land use changes obtained from an advanced version of the GTAP-BIO model for eight biofuel pathways with two emissions accounting models to examine the sensitivity of the ILUC emissions with respect to the changes in LUEFs. These research activities make significant contributions to the existing debates on uncertainties in ILUC emissions values.

[1] The AEZ-EF framework has been developed by Plevin et al. (2014) to convert the GTAP-BIO projections for induced land use changes to ILUC emissions values. The CCLUB framework has been developed by the Argonne National Laboratory in collaboration with the University of Illinois at Chicago (Kwon et al., 2020) for the same purpose. These two different emissions accounting frameworks follow different approaches in determining land use emissions factors.

2. Research method

As noted in the introduction section two different sets of data are required to determine an ILUC for a biofuel pathway: 1) estimated land use changes due to an increase in consumption/production of the fuel produced by the pathway and 2) a set of LUEFs. In general, regardless of differences, the following formula has been implemented to calculate ILUC emissions for a given pathway:

$$ILUC = \frac{\sum_{ikr} \Delta L_{ikr} LUEF_{ikr}}{T \times E}.$$

In this formula, index *i* represents the list of all types of land transitions (e.g., forest to cropland, forest to pasture, etc.), index *k* shows spatial resolution (it could represent national level, agro-ecological level, gride cell, or any other geographical resolution) in each country, and index *r* indicates countries. Variables ΔL, $LUEF$, T, and E are land conversions in hectares, land use emissions factors measured in gCO_2e per hectare, amortization time horizon in years, and annual energy produced by the pathway under study measured in Megajoules, respectively. Therefore, ILUC measures emissions in gCO_2e/MJ. Note that the variable $LUEF$ captures all types of carbon fluxes associated with each type of land conversion.

Hence, in calculating ILUC emissions, one needs to determine ΔL, $LUEF$, T, and E. The last two variables of this list are usually predetermined. However, the first two variables are unknown and should be measured. A sizeable expansion in production or consumption of a biofuel pathway that uses agricultural feedstocks (e.g., corn, soybeans, and many more) could induce land use changes directly or indirectly at local, national, and international levels (Hertel et al, 2010). The size, location, and type of induced land use changes (i.e., ΔL_{ikr}) could vary based on the characteristics of the pathway under consideration such as type of feedstock, location of biofuel production, and fuel conversion technology. However, induced land use changes are not directly observable or measurable. Therefore, economic models have been usually used to assess these land use changes. In this paper, we use the results of a well-known CGE model (GTAP-BIO) to assess land use changes for several aviation biofuel pathways.

In calculating ILUC emissions, one needs to determine the variable $LUEF_{ikr}$ for the *i*, *k*, and *r* indices which is not a trivial task. To accomplish this task, the existing literature has basically relied on the available data sets that provide information on the soil and vegetation carbon contents of alternative types of land cover items by country, region, or fine spatial resolution. A few common data sources in this area of research are IPCC, WINROCK International, Woods Hole, and TEM[2] data sets. In addition to the required data on soil and vegetation carbon stocks, depending on the case under study, one may need additional information or use certain assumptions to mix and match ΔL_{ikr} and $LUEF_{ikr}$variables. To facilitate this process, one may follow different approaches. Since the results of GTP-BIO model are used in this paper, we use two emissions accounting models that have been developed and used to convert the results of this model to ILUC values. These two models are: AEZ-EF model (Plevin et al., 2014)[3] and CCLUB (Kwon et al., 2020). The first carbon account model relies mainly on the IPCC data sources and the second one provides options to follow the WINROCK International or Woods Hole data sources. The CCLUB model also provides some independent assessments for the emission factor associated with cropland pasture, a land category in the GTAP-BIO model, using the Century model. This type of land represents the standard land category of temporary pasture and meadows in the FAO data set.

[2] TEM is a process-based biogeochemistry model. Taheripour and Tyner (2013) have used this model and developed a data set offering land use emission factors for land cover items.
[3] We used a revised version of this accounting model to calculate ILUC emissions for the examined aviation biofuels. As reported by Zhao et al. (2021) the revised AEZ-EF model takes into account changes in the biomass carbon and SOC due to cultivation of dedicated energy crops.

To highlight uncertainties in data on $LUEF_{ikr}$, we first collect and review the existing data sources on the vegetation and soil carbon that have been used in the literature to convert the estimated land use changes to ILUC emissions. These data sources include Woods Hole, Winrock International, IPCC, and sources used by this organization. We next compare the AEZ-EF and CCLUB emissions accounting frameworks, their components, and data sources.

Finally, we calculate ILUC emissions for several aviation biofuel pathways that can be produced in the US by using the estimated land use changes provided by the GTAP-BIO model and the AEZ-EF and CCLUB carbon accounting models. The biofuel pathways represent eight Sustainable Aviation Fuels (SAFs). The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) of the International Civil Aviation Organization (ICAO) has examined ILUC emissions values for these pathways using the AEZ-EF model (Zhao et al., 2021). The eight SAF pathways are:

Soy oil HEFA, Miscanthus FTJ, Switchgrass FTG, Poplar FTJ, Miscanthus ATJ, Switchgrass ATJ, grain ATJ, and grain ETJ. Here we calculate ILUC emissions for these pathways using the AEZ-EF and CCLUB models to highlight their differences.

3. Results

The results show that for a given land type in a geographical region, the existing data sources provide quite different assessments of the vegetation and soil carbon contents. Figure 1 provides some comparisons across the existing data sources on vegetation and soil carbon content for forest and pasture land across the world. The data sources are: AEZ-EF, TEM, and Woods Hole data sets. This figure shows that:

- Regardless of region or data source, the carbon content of forest land is higher than pasture land,

- Regardless of the data source for a given land type, the land carbon content varies significantly across regions. That is because the vegetation cover and soil characteristics vary significantly across regions.
- For a given region and land type, alternative sources provide significantly different estimations for the land carbon content.

The third item mentioned above highlights uncertainties in emissions factors across data sources.

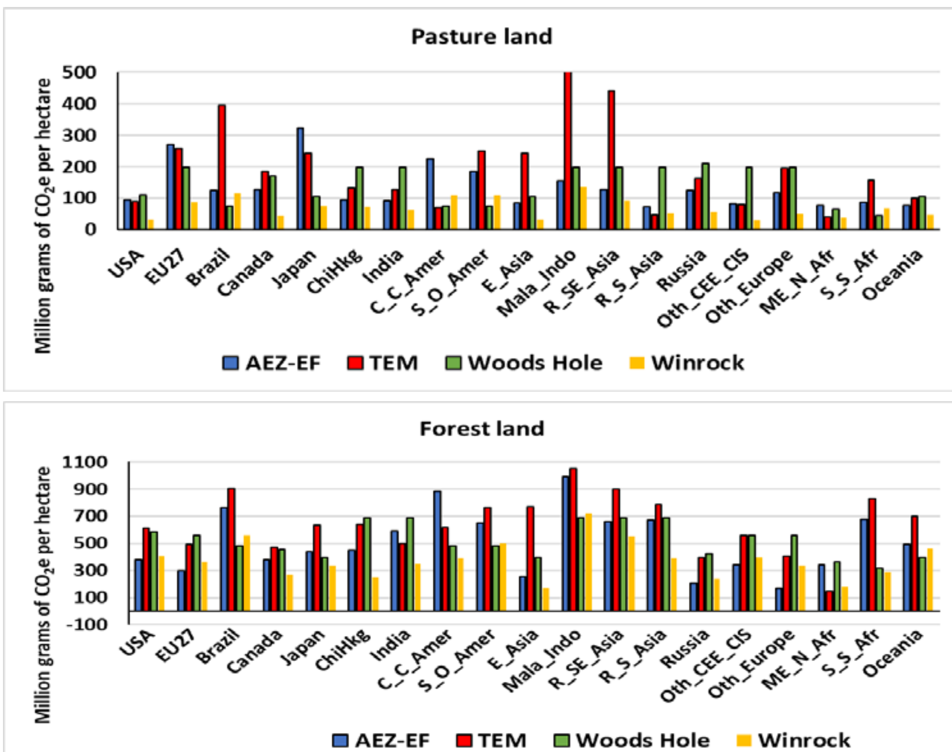

Figure 1. Vegetation and soil carbon content across sources by region

To better assess this line of uncertainty, here we assume the AEZ-EF values as numeraire by calculating the ratios of TEM/AEZ-EF and Woods Hole/AEZ for each type of land in each region. Figure 2 shows the results. As shown in this figure, the ratios for both forest and pasture deviate significantly from the numeraire (value of 1 on the vertical axis) across regions. This suggests that differences across alternative sources of land carbon content in many cases are large. This indicates that using alternative sources of land carbon content could lead to major uncertainties in assessing ILUC values.

Here we provide some specific examples for differences in emissions factors across alternative sources. In the Woods Hole data set, the emissions factor of converting forest to cropland for Malaysia and Indonesia is about 690 metric tons of CO_2e per hectare. The corresponding value in the AEZ-EF framework is about 1000 metric tons of CO_2e per hectare, 45% higher than the Woods Hole data set value. The corresponding difference for the pasture land is about -25%. The annual foregone sequestration rate is about 0.84 metric tons of carbon per hectare for the European Boreal forest in the AEZ-EF framework. The corresponding rate obtained from the IPCC reference tables varies between 0.2 to 0.6 tons of carbon per hectare.

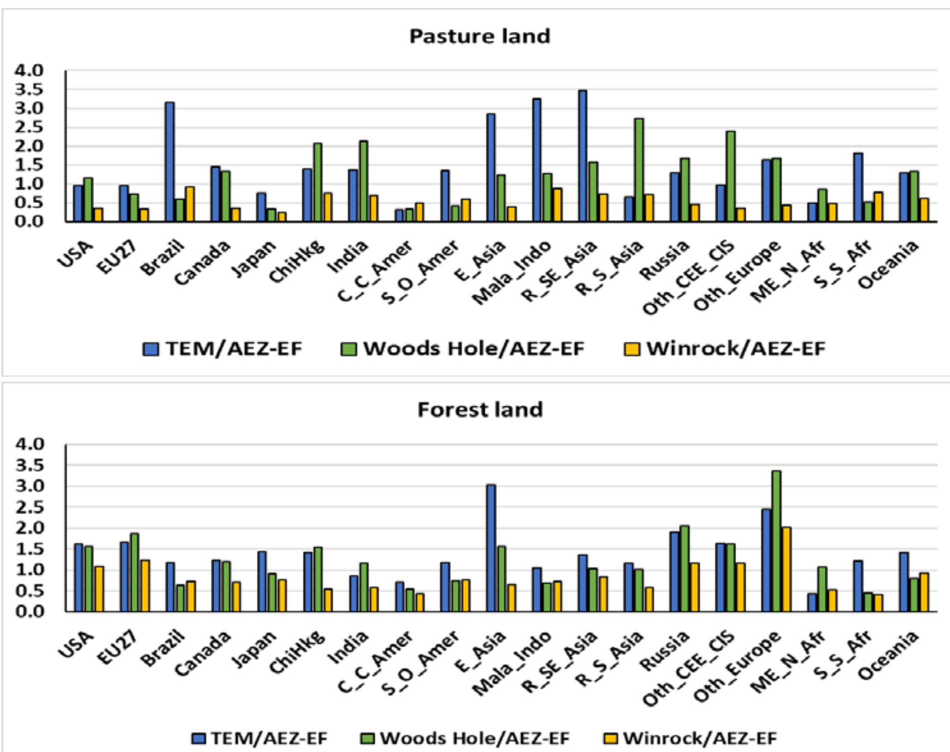

Figure 2. Ratios of TEM/AEZ-EF, Woods Hole/AEZ-EF, and Winrock/AEZ-EF for land carbon content

The carbon accounting models such as AEZ-EF and CCLUB rely on the IPCC reports and guidelines to determine their emission factors. However, the IPCC revises its data sets and guidelines over time. These revisions suggest that data sources on soil and vegetation carbon contents are uncertain and subject to reassessments over time. To highlight this fact, consider Figure 3 which shows percent differences in the IPCC default reference values for soil organic carbon stocks (SOC_{REF}) for mineral soil presented in the 2019 and 2006 guidelines for various soil types and climate regions. This figure indicates that in most cases the default SOC_{REF} values declined in the new IPCC guideline. This suggests that those models that used the 2006 IPCC reference values on SOC need to adopt the newer SOC values provided by the 2019 IPCC report to avoid overestimating ILUC emissions.

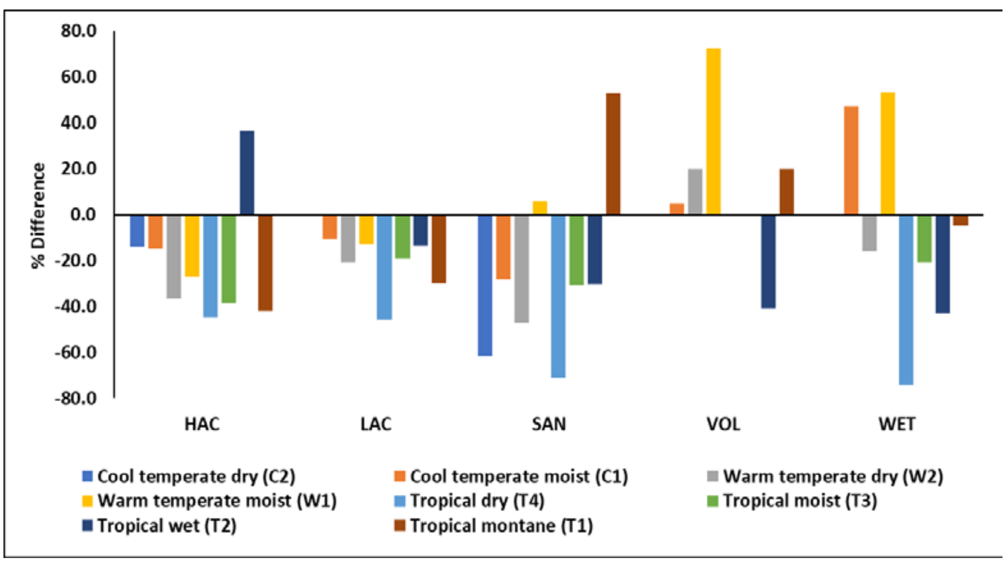

Figure 3. Percent differences in the IPCC default reference values for soil organic carbon stocks (SOC_{REF}) for mineral soil presented in the 2019 and 2006 guidelines for various soil types and climate regions. Here HAC, LAC, SAN, VOL, and WET stand for High activity clay soils, Low activity clay soils, Sandy soils, Volcanic soils, and Wetland soils, respectively. % differences are [(SOC_{REF} of 2019 - SOC_{REF} of 2006)/SOC_{REF} of 2006]*100.

We now present the calculated ILUC emissions for the eight SAF pathways using the AEZ-EF and CCLUB carbon accounting models in Table 1. This table shows the ILUC emissions measured in

gCO_2 e/MJ assuming a 25-year amortization time horizon. As shown in this table the ILUC values obtained from these two emissions accounting modes are quite different across the examined pathways. First consider the results for the soil oil HEFA, grain ATJ and grain ETJ pathways. For these pathways, the CCLUB model provides lower ILUC emissions compared to the AEZ-EF model. That is mainly because the CCLUB takes into account improvements in the soil organic carbon content of cropland pasture due to conversion of this type of marginal to crop production. For this type of land, the AEZ-EF model in an ad hoc manner assumes that conversion of cropland pasture to crop production releases carbon with an emission factor half of the emission factor for pasture land.

Table 1. Estimated ILUC values for various SAF pathways using different emissions accounting models for a 25-year amortization time horizon (gCO_2 e/MJ)

Pathways	ILUC obtained from AEZ-EF model						ILUC Obtained from CCLUB	Difference: AEZ-EF - CCLUB
	Natural Vegetation	Foregone Sequestration	Soil Organic Carbon	Biomass Carbon	Peat Oxidation	AEZ-EF Total		
Soy oil HEFA	8.0	0.6	5.0	1.6	4.9	20.0	15.0	5.0
Miscanthus FTJ	12.5	1.5	-33.6	-17.8	0.2	-37.3	-12.8	-24.5
Switchgrass FTJ	18.1	2.5	-17.3	-11.8	0.3	-8.2	1.0	-9.2
Poplar FTJ	15.4	2.2	-7.8	-19.5	0.2	-9.6	7.0	-16.6
Miscanthus ATJ	16.1	1.6	-51.0	-25.3	0.1	-58.5	-26.1	-32.3
Switchgrass ATJ	25.1	3.0	-28.7	-18.5	0.3	-18.9	-14.1	-4.7
Grain ATJ	12.5	1.5	8.4	-0.3	0.3	22.5	14.4	8.1
Grain ETJ	13.9	1.6	9.4	-0.3	0.4	24.9	15.6	9.3

For the dedicated energy crop pathways, the modified AEZ-EF provides significantly lower ILUC emissions than the CCLUB model. For these pathways, the AEZ-EF assigns improvements in SOC per hectare of converted land to the dedicated crop under study. However, the CCLUB only considers improvements in SOC of cropland pasture. To highlight the implication of this difference, consider the column of Soil Organic Carbon in Table 1. This column shows that the

AEF-EF model assesses significantly large negative changes in SOC for dedicated crops. A match between the approaches followed by these models will lead to lower differences between their results for the pathways that use dedicated energy crops as feedstock.

As mentioned above, Table 1 shows ILUC values for a 25-year amortization time horizon. However, the US biofuel policies consider a 30-year amortization time horizon. Table 2 provides the IULC values for the examined pathways for 25-year and 30-year amortization time horizons.

As shown in Table 2, a 30-year amortization time horizon leads to lower ILUC values for all pathways and for both the AEF-EF and CCLUB models.

Table 2. Estimated ILUC values for various SAF pathways using different emissions accounting models for 25- and 30-years amortization time periods (gCO_2 e/MJ)

Pathways	Amortization time horizon			
	25 years		30 years	
	AEZ-EF	CCLUB	AEZ-EF	CCLUB
Soy oil HEFA	20.0	15.0	16.6	12.5
Miscanthus FTJ	-37.3	-12.8	-31.1	-10.7
Switchgrass FTJ	-8.2	1.0	-6.8	0.9
Poplar FTJ	-9.6	7.0	-8.0	5.9
Miscanthus ATJ iBuOH	-58.5	-26.1	-48.7	-21.8
Switchgrass ATJ iBuOH	-18.9	-14.1	-15.7	-11.8
Grain ATJ	22.5	14.4	18.7	12.0
Grain ETJ	24.9	15.6	20.8	13.0

4. Conclusions

This paper shows that while the existing literature has extensively discussed uncertainties in assessing induced land use changes due to biofuels, no major effort has been made to evaluate uncertainties in land use emission factors. The paper indicates that variations in the available data sources that provide land use emission factors are substantially large. Moving from one data source to another one significantly affects the estimated ILUC emissions, for a given set of estimated land use changes for a given pathway. The paper also shows that the AEZ-EF and CCLUB model provide different assessments for ILUC emissions again for the same estimated land use changes. Finally, we highlighted the causes of the differences between the results of these models.

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