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Spatially-explicit land use change emissions and carbon payback times of biofuels under the Carbon Offsetting and Reduction Scheme for International Aviation

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Abstract

The Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) requires airlines to offset their greenhouse gas (GHG) emissions above 2019 levels by either buying carbon offsets or using Sustainable Aviation Fuels (SAFs). These are drop-in jet fuels made from biomass or other renewable resources that reduce GHG emissions by at least 10% compared to kerosene and meet sustainability criteria. This study assesses the direct land use change (DLUC) emissions of SAF, i.e., GHG emissions from on-site land conversion from previous uses (excluding primary forests, peatlands, wetlands, and protected and biodiversity-rich areas) into alternative feedstocks, considering spatial variability in global yields and land carbon stocks. The results provide DLUC values and carbon payback times at 0.5-degree resolution for six SAF pathways, with and without irrigation and medium-input intensity, according to CORSIA sustainability criteria. When excluding CORSIA non-compliant areas, soybean SAF shows the highest mean DLUC factor (31.9±20.7 gCO_2/MJ), followed by reed canary grass and maize. Jatropha SAF shows the lowest mean DLUC factor (3.6±31.4 gCO_2/MJ), followed by miscanthus and switchgrass. The latter feedstocks show potential for reducing GHG emissions over large areas but with relatively greater variability. Country-average DLUC values are higher than accepted ILUC ones for all pathways except for maize. To ensure the GHG benefits of CORSIA, feedstocks must be produced in areas where not only carbon stocks are relatively low but also where attainable yields are sufficiently high. The results help identify locations where the combination of these two factors may be favourable for low-DLUC SAF production. Irrigated miscanthus offers the highest SAF production potential (2.75 EJ globally) if grown on CORSIA-compliant cropland and grassland areas, accounting for ~1/5 of the total kerosene used in 2019. Quantifying other environmental impacts of SAFs is desirable to understand sustainability trade-offs and financial constraints that may further limit production potentials.

Keywords: carbon offsetting, corsia, greenhouse gas, international aviation, jet fuel, sustainable aviation fuel

1. Introduction

The aviation sector has been growing steadily, by ~3% annually, since the 1970s (Fleming & de Lépinay, 2019), reaching 4.3 billion passenger journeys in 2018 (Klöwer et al., 2021). In that year, global aviation consumed approximately 320 Mt of fuel and emitted one Gt of CO_2 (Gössling & Humpe, 2020). NOx and H_2O emissions, soot and sulphate particles, and persistent linear contrails also contribute to radiative forcing and climate change (Lee et al., 2009). International aviation accounted for ~2.4% of global anthropogenic greenhouse gas (GHG) emissions and 3.5% of total radiative forcing in 2018 (Lee et al., 2021). In 2022, global CO_2 emissions from aviation regained nearly 80% of the drop seen during the pandemic, reaching ~800 Mt (IEA, 2023). Forecasts indicate that aviation traffic will grow between 2.3% to 3.3% per annum between 2019 and 2050, catching up with pre-pandemic trends (ATAG, 2021). While emissions from domestic aviation are covered by the Paris Agreement, emissions from international civil aviation are outside the scope of countries' pledges. It is the International Civil Aviation Organization (ICAO) that quantifies these emissions and sets technical and environmental goals towards the carbon-neutral growth of the sector. In 2016, country members of the ICAO adopted the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), aimed to cap international aviation emissions at their 2019 levels (ICAO, 2019). Following the International Air Transport Association's (IATA) resolution (IATA, 2021), ICAO has approved the long-term aspirational goal (LTAG) to achieve net-zero carbon emissions from international aviation by 2050 (ICAO, 2022a).

Voluntary from 2021 to 2027, CORSIA requires airlines to either buy carbon offsets or use sustainable aviation fuels (SAFs) and lower-carbon aviation fuels (LCAFs) in replacement of fossil kerosene. SAFs are jet fuels derived from renewable resources such as biomass or waste, produced through pathways certified by the American Society for Testing and Materials (ASTM) (Prussi et al., 2021). These include hydroprocessed esters and fatty acids (HEFA) from fats, oils and greases; or Fischer-Tropsch (FT), alcohol-to-jet (ATJ), and hydroprocessed fermented sugars to synthetic isoparaffins (HFS-SIP), all from lignocellulosic and starch-based feedstock (Capaz et al., 2020; ICAO, 2022b; Seber et al., 2022).

Alcohol-to-jet pathways can use either ethanol (i.e., ethanol-to-jet, ETJ) or iso-butanol as an intermediate input, according to ASTM. LCAFs are fossil-based fuels that have lower life cycle GHG emissions than the reference fossil kerosene. Both SAFs and LCAFs must meet additional sustainability criteria to be certified according to the Sustainability Certification Scheme (SCS) (ICAO, 2020, 2022c). Using SAFs is considered the most feasible option to meet the LTAG in the medium term, contributing up to 71% GHG emissions reductions in an ambitious technology deployment scenario (ICAO, 2022d). The percentage of SAFs in jet kerosene for aviation remains very small (<0.1%) (IEA, 2023), mainly due to their limited cost-competitiveness (Ng et al., 2021).

SAFs have, in principle, a favourable GHG balance relative to fossil kerosene, as feedstock production sequesters carbon in crop biomass and the carbon released through combustion is biogenic. However, agricultural practices undermine these benefits by altering the soil carbon balance and removing crop biomass through regular harvest (Elshout et al., 2015; Liska et al., 2014). The crop establishment releases GHG emissions when carbon stocks are lost relative to previous uses, especially when forests are converted (Field et al., 2020; Harris et al., 2015). This is known as direct land use change (DLUC), which refers to carbon stock changes in soil and biomass in the area where the biofuel feedstock is grown. Some studies propose to use spatially-explicit data to improve the representation of DLUC and subsequent GHG emissions (Escobar et al., 2020; Garofalo et al., 2022). Increasing demand for crop biomass can also lead to higher crop prices and subsequent land transformation between croplands, grasslands, and forests globally (Hertel & Tyner, 2013; Tonini et al., 2012). This market-mediated land conversion across uses is commonly known as indirect (or induced) land use change (ILUC) and must be estimated by means of economic modelling combined with biophysical modules (Escobar & Britz, 2021; Zhao et al., 2021).

CORSIA sustainability criteria establish objectives across fourteen thematic areas (e.g., GHG emission reductions, carbon stocks and soil conservation, agricultural practices, biodiversity conservation, indigenous rights, food security, etc.). To certify eligible SAFs through the CORSIA pilot phase, only compliance with Themes 1 and 2 must be proven on the basis of independent attestation by SCSs (ICAO, 2020, 2022c). These include the following criteria: 1.1) SAFs must deliver GHG savings of at least 10% relative to fossil kerosene; 2.1) not be produced at the cost of land classified as primary forests, wetlands, or peatlands after 1 January 2008; 2.2) be associated with a DLUC value in the event of land conversion after 1 January 2008. Life cycle GHG emissions (excluding DLUC and ILUC), referred to as core-LCA values, are estimated from well to wake based on attributional life cycle assessment (ALCA) with energy allocation. SAF producers must calculate their GHG emissions by using either the CORSIA methodology (ICAO, 2022e) or the approved core-LCA and ILUC values (ICAO, 2022f). The latter two are estimated per feedstock and pathway by experts within ICAO's Committee on Aviation Environmental Protection (CAEP). ILUC values are quantified with two widely-known global economic models according to the ICAO protocol, and only the results from the respective modelling teams are considered by the ICAO Council (ICAO, 2022b). As for DLUC estimation, CAEP developed general guidelines based on IPCC (2019), which consider DLUC any land conversion from previous uses into SAF feedstock production. If DLUC emissions exceed the accepted ILUC value, the DLUC value shall be used to calculate the GHG savings. If the sum of DLUC and core-LCA values does not satisfy CORSIA sustainability criterion 1.1, the land types affected are classified as ineligible for SAF production. The remaining sustainability themes (3-14) will become relevant in the post-pilot phase of CORSIA.

Although DLUC estimation does not require consequential LCA modelling, under the IPCC approach, DLUC values are subject to many assumptions, e.g., regarding land uses to be replaced, biomass productivity after land conversion, as well as the choice of data sources. Unlike for ILUC calculation, there is no CORSIA protocol or harmonization process proposed to calculate accepted DLUC values for different feedstocks and sourcing regions. DLUC emissions have been extensively assessed in the context of road biofuels, assuming land uses converted in the sourcing regions, underlying carbon stocks and average crop management practices under the IPCC Tier 1 approach (Castanheira et al., 2015; Malça et al., 2014; Puricelli et al., 2021). All these factors prove more decisive in determining the GHG emission intensity of SAF than other critical ALCA modelling choices such as allocation (Capaz et al., 2021; Seber et al., 2022). Few LCA studies use spatial analysis to assess the role of DLUC in the GHG balance and production potentials of biofuels in EU marginal lands (Iordan et al., 2023; Vera et al., 2021). Perennial crops and grasses often reduce DLUC emissions through carbon gains in crop biomass and soil (Don et al., 2011; Iordan et al., 2023; Vera et al., 2021). The carbon payback time (CPT) is also used in the literature to quantify the time it takes for GHG savings from fossil substitution to offset DLUC emissions (Fargione et al., 2008). Based on relative crops' suitability areas in Brazil, Lapola et al. (2010) found shorter CPTs for oil palm, jatropha, and sugarcane than for soybean, especially if grown at the cost of grasslands/shrublands. Elshout et al. (2015) and Gibbs et al. (2008) estimated spatially-explicit CPTs for crop-based biofuels, considering natural land conversion into feedstock production. Both studies show shorter CPTs for high-yielding perennial crops (sugarcane, oil palm). Only Gibbs et al. (2008) included non-food crops such as castor, while lignocellulosic crops were not evaluated.

In view of the lack of evidence and agreement on the calculation of DLUC emission intensities of SAF, this work aims to quantify DLUC values and associated variability for six CORSIA feedstocks, including both food and non-food crops. Results provide the first and most up-to-date spatially-explicit estimates of global DLUC emissions and CPTs of SAFs, excluding land conversion at the cost of carbon- and biodiversity-rich ecosystems. The goal is to assess if jet fuels from these crops fulfil the CORSIA sustainability criteria, considering spatial variability in yields and land carbon stocks. Results show those areas where DLUC can compromise the GHG benefits from SAF production, giving and indication on where these feedstocks could be grown to be eligible for CORSIA and promote the carbon-neutral growth of the aviation sector.

2. Methods

DLUC emissions are estimated as GHG emissions (removals) from land converted into feedstock cultivation for SAF production at Tier 2 level, following the IPCC guidelines (IPCC, 2006, 2019). GHG emissions arise from differences in carbon stock across pools – above- and below-ground biomass

(AGB, BGB) and soil organic carbon (SOC) –, before and after land conversion, considering the observed land use distribution in each pixel as the baseline. Emissions from biomass burning are excluded due to the lack of information on global areas burnt (ICAO, 2022e). Net carbon losses (gains) are annualized taking an amortization period of 25 years. This is arbitrarily chosen by CAEP to represent the time that it takes to amortize GHG emissions from DLUC in the future. Annualized DLUC emissions are estimated as tCO_2/ha and ultimately expressed as gCO_2/MJ, considering crop yields and conversion efficiencies throughout the production pathways, as well as energy allocation between co-products. Six feedstocks considered by CORSIA are evaluated: two oilseed crops (jatropha and soybean), three lignocellulosic grasses (miscanthus, switchgrass, reed canary grass – RCG), and one starch-based crop (maize). These are chosen based on the availability of attainable yield data on a global scale. Non-food feedstocks are supposed to have lower, even negative, ILUC values compared to soybean and maize, which are assessed as the commercial reference food feedstocks.

The method described provides DLUC results in line with CORSIA criterion 2.1, as well as 7.1, i.e., SAFs should not made from biomass produced in protected areas with high biodiversity or conservation value (ICAO, 2022c). Results allow identifying those locations in which DLUC>ILUC value (criteria 2.2) and where SAFs deliver reductions in life cycle GHG emissions of 10%, relative to fossil kerosene (criteria 1.1), with and without core-LCA emissions. Only RCG has no accepted values for either ILUC or core-LCA in CORSIA, hence the latter had to be estimated. The data used and major assumptions are explained in this section, while the DLUC calculation steps are shown in the Annex (eq. 1-7). Emissions from biomass burning, forgone carbon sequestration, and changes in dead wood and litter are excluded, as these are highly variable and depend on forest type and age, disturbance history and management (IPCC, 2006).

2.1. Spatially-explicit data processing

DLUC emissions are calculated at 0.5-degree resolution (30 arc-min, 50x50 km) based on observed land uses and carbon stocks in each pixel in the period 2010-2015 (Jung et al. 2021), hence capturing land conversion after 1 January 2008. The land uses include a mix of secondary forests, forest plantations, shrublands, herbaceous vegetation, moss and lichen, cropland, pasture and bare/sparse vegetation. Jung et al. (2021), in turn, combined several data sources at 1x1 km resolution, namely: Buchhorn et al. (2020) for the spatial distribution of vegetation classes in 2015; Santoro et al. (2021) for AGB in 2010; and IPCC (2006) for BGB based on adjusted root-to-shoot ratios. For this analysis, intact or biodiversity-rich areas, primary forests, peatlands, and wetlands were excluded, applying the same global carbon and conservation potential layers for biodiversity-rich areas as Jung et al. (2021). Specifically, primary forests and biodiversity-rich areas were excluded by intersecting global landscapes data (Potapov et al., 2017) with the top 10% areas with the highest biodiversity conservation potential. The effect of forest management on biomass density was also taken into account based on a remotely-sensed forest management layer consistent with the land use distribution in the same period (Lesiv et al., 2022). SOC data was derived from the Harmonized World Soil Database (HWSD v1.21) (Nachtergaele et al., 2012). Additional assumptions from the global gridded crop modelling framework EPIC-IIASA (Balkovič et al., 2014; Carr et al., 2020; Folberth et al., 2016) were applied to derive the SOC stock in the topsoil layer, ranging from 10 to 30 cm, depending on the soil type given by HWSD and the volume of stones. The SOC stock was calculated for the area-dominant soil type in each spatial simulation unit in EPIC-IIASA, based on the topsoil depth (cm), SOC content (%), and bulk density (g/cm^3). Spatial simulation units are clusters of 5 arc-min pixels (ranging in size from 5'x5' to 0.5°x0.5°) that belong to the same country, have similar altitude, slope, and soil characteristics (IIASA-IBF, 2023; Skalsky et al., 2008). Only carbon stocks in mineral soils are considered, as organic soils are ineligible for growing SAF feedstock for CORSIA.

Spatially-explicit yields are taken from the Global Agro-Ecological Zone (GAEZ) v4 portal (Fischer et al., 2021), with 5 arc-min resolution (9x9 km). Attainable yields in current cropland areas in the period 1981-2010 were used, both in rainfed and irrigated conditions, assuming CO_2 fertilization. This period is associated with less uncertainty than the next available one (i.e., 2011-2040) and delivers country-average yields in line with those considered for the respective core-LCAs (Table S1.1 in the Electronic

Supplementary Material – ESM). Attainable yields are, in turn, modelled by using crop models with assumed agricultural practices, irrigation, and input application doses. The specific crop systems determine the water supply, based on crop evapotranspiration and soil moisture balances, considering edaphoclimatic characteristics and terrain suitability (Nachtergaele et al., 2012). GAEZ v4 also simulates climate effects on crop productivity and water regimes (rainfall and irrigation), considering fallow periods, which influence the water balances and attainable yields for historical, current and future climates. It must be noted that attainable yields are those potentially obtained considering agrological and edaphoclimatic characteristics and do not necessarily correspond to observed yields in the same period. In other words, GAEZ v4 attainable yields capture those areas where the production of each feedstock is feasible from the agro-climatic point of view, under the assumed crop management. Thus, yield variability is exclusively due to the edaphoclimatic characteristics of the site, while crop management does not vary with the location. Feedstock-specific suitability areas are then defined as the extension in which crops can grow either rainfed or with irrigation, i.e., where attainable yields are estimated in GAEZ v4, also excluding protected areas, lakes and wetlands (Fischer et al., 2021). The distinction between irrigated and rainfed conditions aims to represent two alternative scenarios for potential yields and distribution areas for each feedstock (Figure S1.2). It does not give information on the preferred irrigation regime, nor on the financial viability in each pixel. For irrigated maize, yields with sprinkler irrigation are used, as this option is more efficient and delivers larger suitability areas than gravity systems (D'Odorico et al., 2020; FAO, 2012; Grote et al., 2021). All above-mentioned data were finally processed at 0.5-degree resolution (50x50 km), calculating weighted averages based on the respective suitability areas, and integrated into the GLOBIOM modelling framework (IIASA-IBF, 2023).

2.2. Additional data and assumptions

SOC losses (gains) arise from changes in land management relative to the reference soils, assuming that SOC reaches an equilibrium value specific to the soil, climate, and land use after the conversion.

Reference soils are defined as those under potential vegetation, neither degraded nor improved (IPCC, 2006). In this analysis, reference soils are those represented by Nachtergaele et al. (2012), corresponding to the period 1971-1982. In the absence of spatially-explicit data on crop management, default IPCC Tier 1 coefficients (IPCC, 2019) were mapped with the climatic zones in GLOBIOM to represent the effect of agricultural practices on SOC after land conversion into SAF. It was assumed that annual crops are produced with medium input intensity and full tillage, and perennials with medium input intensity and reduced tillage, in line with GAEZ v4 yield data. Alternative scenarios are assessed and discussed in section 4, also using the IPCC (2006) coefficients. DLUC estimates thus combine spatially-explicit carbon stock and yield data at Tier 2 level with default IPCC Tier 1 coefficients for SOC change. In the absence of spatially-explicit and globally consistent data, carbon sequestration in SAF feedstock after land conversion (hereinafter referred to as *living biomass*) was assumed from the literature, based on the assumed crop management and GAEZ v4 average yields (Tables S1.1-S1.2).

2.3. Production pathways and co-products

Following CORSIA, DLUC emissions are energy-allocated among the several co-products (when available) based on their relative lower calorific values (LHVs). This requires identifying the co-products generated along the life cycle and their major applications, which are both feedstock- and pathway-specific (Figure S1.1). The same assumptions as those agreed by CAEP for modelling CORSIA pathways have been applied (ICAO, 2022b). These determine both the allocation factors and core-LCA emissions (Tables S1.5 and S1.6). Processing oilseeds into HEFA delivers protein meal as a co-product from oil extraction. Soybean meal constitutes the most important protein source used in feed rations worldwide (De Maria et al., 2020). Jatropha meal is used for animal feed after detoxification, while husk and shell are used to produce electricity through combustion. Although CORSIA also considers two additional scenarios for jatropha meal applications (fertilizer or electricity generation), only the use as feed is considered, for being more comparable to the soybean-HEFA pathway. Lignocellulosic and starch-based crops are assumed to be used in ETJ pathways via ethanol conversion. Straw from lignocellulosic crops is employed for on-site energy generation through a combined heat and power system in a standalone facility. The surplus electricity is then sold to the grid. ETJ production from maize delivers dried distillers' grains with solubles (DDGS), used in feed concentrates. Jet fuel synthesis both in HEFA and ETJ pathways also co-produces diesel and naphtha. Pathway-specific allocation factors, conversion efficiencies, and other data needed for the DLUC factor estimation are shown in the ESM (Tables S1.3-S1.5).

2.4. Core-LCA emissions, carbon payback times and SAF production potentials

To identify areas compliant with the sustainability criterion 1.1, GHG savings per MJ of SAF are quantified for each feedstock and pathway by combining the estimated DLUC factors with core-LCA values, with the latter covering the remaining well-to-wake GHG emissions. As in CORSIA, a single core-LCA value is used for each feedstock, which corresponds to irrigated production (ICAO, 2022b). Core-LCA values from CORSIA are used, i.e., global values, when available. The core-LCA value for RCG-ETJ was estimated following the methodology and assumptions in section 2.2, since this pathway does not yet have an accepted value (Table S1.6 in ESM). GHG savings relative to the CORSIA fossil comparator (89 gCO_2eq/MJ) are ultimately used to estimate spatially-explicit CPTs as a complementary metric on the DLUC emission implications from SAF production. The CPT is defined as the time that it takes for the GHG benefits from fossil kerosene substitution with SAF to compensate for total GHG emissions from land conversion as a one-time effect. CPTs are quantified by dividing DLUC emissions (before amortization) by the annual GHG savings (excl. DLUC) relative to fossil kerosene (eq. 8 in the Annex). Finally, SAF production potentials are calculated for each feedstock, considering that the crop grows in agricultural land available in CORSIA-compliant areas and the corresponding attainable yields with and without irrigation (eq. 9). Two alternative scenarios are defined: one in which each feedstock is produced on available cropland areas, and one in which each feedstock is produced on available cropland and grassland areas.

3. Results

3.1. DLUC emissions across eligible areas (criteria 2.1 and 7.1)

DLUC emission factors are firstly estimated as tCO_2eq/ha (DLUC1 in eq. 6 in the Annex) for each pixel within each crop's eligible areas according to criteria 2.1 and 7.1, shown in Figure 1 for irrigated feedstocks only. Empty pixels correspond to either non-suitable areas, i.e., where production is not agronomically feasible (see Figure S1.2), or to non-eligible pixels. Results in tCO_2eq/ha help understand the uncertainty in DLUC strictly due to spatial variability in land carbon stocks, without reflecting the effect of yields. Thus, the highest DLUC factors are found in pixels with relatively larger carbon stocks, especially in vegetation. DLUC emissions for rainfed feedstocks are in the ESM (Figure S2.1), which vary only in terms of the extent of eligible areas, while the carbon stocks per pixel are the same.

The feedstocks that grow in tropical and subtropical latitudes (soybean, jatropha, miscanthus, and maize) show the highest values across the Congo and Amazon River basins and Southeast Asia (Figure 1), associated with the clearing of secondary forests and shrublands. The highest DLUC factors for RCG and switchgrass are found in temperate areas of North and South America. These two feedstocks have the highest mean DLUC factors, i.e., 3.0±2.6 and 1.9±2.4 tCO_2/ha, respectively (DLUC1 in Table S2.1). The lowest mean DLUC factor is estimated for miscanthus (1.4±2.8 tCO_2/ha), followed by jatropha (1.4±2.8 tCO_2/ha) and maize (1.4±1.4 tCO_2/ha). This indicates that the sustainability criteria 2.1 and 7.1 effectively exclude the most carbon-rich land uses (particularly high in tropical locations) but still include relatively carbon-rich secondary forests, especially in temperate climates where RCG and switchgrass primarily grow. Mean vegetation stocks in eligible areas for jatropha are 23.2 tC/ha, while they are 25.5 tC/ha for RCG. Similarly, soils in temperate latitudes are richer in carbon than tropical soils, which contributes to the DLUC emissions. The mean SOC content in eligible areas is the highest for RCG (47.9 tC/ha) and the lowest for jatropha (38.8 tC/ha). The decomposition of the DLUC factors into carbon pools (vegetation vs. SOC) is included in ESM (Figure S2.2, with irrigation). DLUC emissions from SOC changes vary between -2 and 13 tCO_2/ha for perennials. Negative values are found within the tropics, mainly for jatropha and miscanthus, while updated IPCC coefficients estimate SOC losses from perennials in both temperate and polar latitudes through the Flu coefficient – in contrast to IPCC (2006). Annual crops plus switchgrass, which does not show eligible areas within the tropics, cause SOC losses and associated emissions (up to 13 tCO_2/ha) under the crop management assumptions in section 2.2. However, emissions from vegetation loss are the largest contributor to DLUC in the pixels with the highest values, i.e., on average, more than 75% in the top decile for all crops.

The widest range of DLUC factors is found for miscanthus (-2.5–19.8 tCO_2/ha), followed by jatropha (-2.3–18.4 tCO_2/ha) (Table S2.1). For these two crops, values in the top decile (>5.2 tCO_2/ha, respectively) lie mostly between the tropics or in subtropical regions of the US, with a few exceptions. On the contrary, soybean and maize show the smallest DLUC ranges, from -0.1 tCO_2/ha to 10.9 tCO_2/ha for maize (12.8 tCO_2/ha for soybean). These two crops benefit from the lower allocation coefficients to the intermediate product relative to the other feedstocks, which translates into a smaller share of DLUC emissions allocated to the jet fuel (Table S1.5). As a result, maize and soybean show relatively lower DLUC values in the top decile (>3.4 and >4.0 tCO_2/ha, respectively); again, mainly across the tropics and the US, with exceptions in South America, Europe, and Russia. Switchgrass and RCG have DLUC emissions respectively ranging from -1.0 and -0.6 tCO_2/ha to 18.9 tCO_2/ha. These crops have DLUC factors in the top decile (>5.5 and >6.9 tCO_2/ha, respectively) distributed across Europe, North America, and Central Asia.

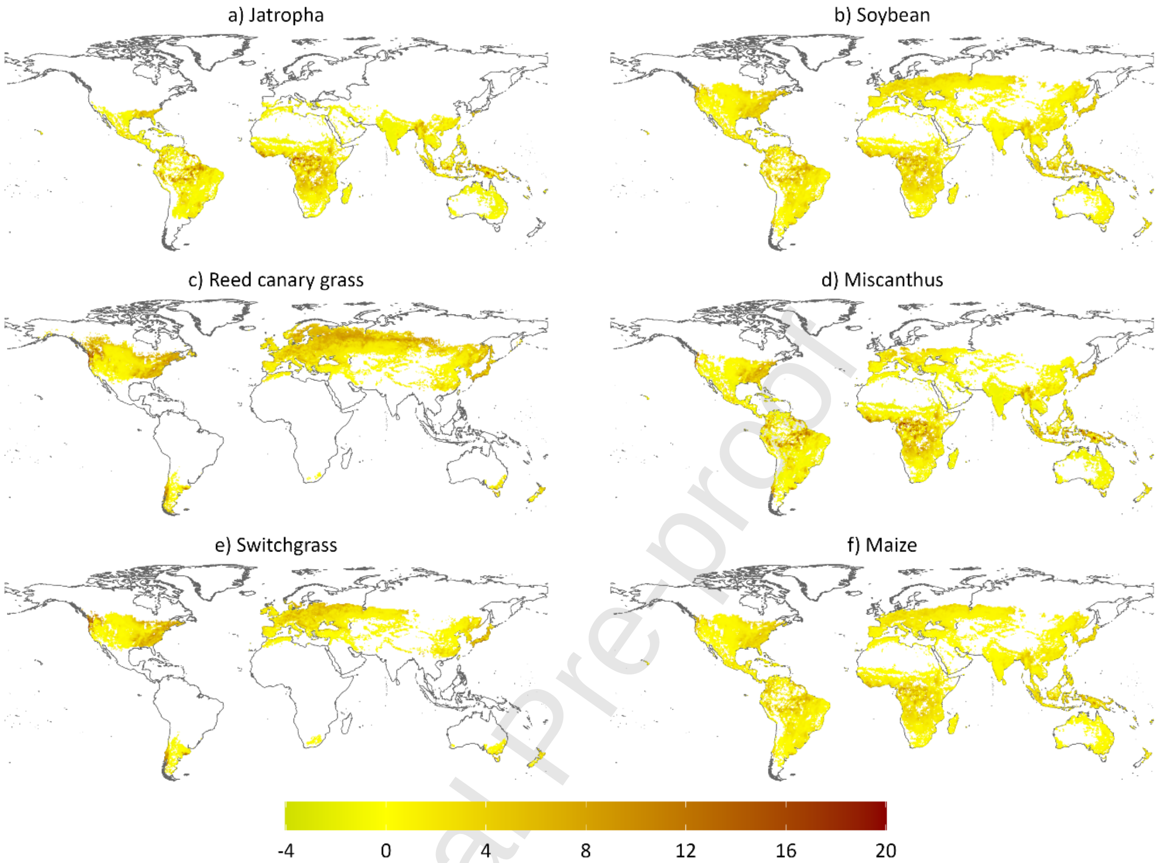

Figure 1. Direct land use change (DLUC) emissions (tCO_2eq/ha), after allocation and amortization, for feedstocks grown with irrigation, excluding primary forests, peatlands, wetlands, and protected and biodiversity-rich areas.

Perennial feedstocks show greater potential to deliver negative DLUC factors through carbon sequestration in soil and living biomass, especially where carbon stocks in vegetation are low. DLUC values in the lowest decile are all negative for jatropha, miscanthus, and switchgrass (Table S2.1). Miscanthus and jatropha yield negative DLUC factors in 40% and 41% of the eligible area, while this share is much lower for switchgrass (15%) and RCG (3%). On the one hand, this is related to the relatively lower carbon sequestration in living biomass by the latter two (Table S1.2); on the other hand, to their larger eligible areas in temperate (polar) regions, in which perennial crop production yields SOC losses (positive CO_2 emissions) with 2019 IPCC coefficients. This makes switchgrass and RCG have similar SOC effects to annual crops when grown in temperate climates. RCG causes greater SOC losses in temperate dry climates, with a greater contribution to DLUC (Table S1.5). Soybean and maize deliver negative DLUC values in 0.9% and 2.6% of the eligible pixels, since annual crop production (with full tillage and medium input intensity) is associated with SOC losses under IPCC Tier 1, regardless the climatic zone, and living biomass is not enough to outweigh AGB and BGB losses.

3.2. CORSIA-compliant DLUC factors (criteria 1.1, 2.1 and 7.1)

Compliance with criterion 1.1 must be evaluated by estimating DLUC in gCO_2/MJ (DLUC2 in eq. 7). Uncertainty in DLUC emissions is due to spatial variability in both land carbon stocks and crop yields, with yields close to zero in some locations (Figure S1.2). Pixels with yields below the first quartile[1] (<15th percentile for switchgrass) are excluded from the analysis, for being considered too low from the financial point of view, based on the literature (Tables S1.1-S1.2). For switchgrass, GAEZ v4 attainable yields are high compared to those in the literature, mainly capturing production on marginal lands (see Table S1.1). Figure 2 shows pixels where DLUC factors (on the left) and total GHG (DLUC + core-LCA emissions, on the right) meet the 10% GHG reduction criterion across eligible areas for irrigated crops, while the rest are greyed out. Figure 2 shows the reduction in eligible areas relative to Figure 1 when CORSIA sustainability criterion 1.1 is included, applied to total GHG or to DLUC emissions only.

Miscanthus, switchgrass and maize keep more than 70% of the eligible areas in Figure 1 also compliant with criterion 1.1, when only considering DLUC emissions. This percentage is lower for RCG (63%), jatropha (58%), and soybean (53%). Non-compliant areas are found around the Amazon and Congo

[1]This rule excludes pixels with yields <1.4 t seed/ha for jatropha; <2.1 t seed/ha for soybean; <3.4 t/ha for maize; <7.0 t/ha for reed canary grass; <8.7 t/ha for miscanthus, <6.0 t/ha for switchgrass; which are considered very low in relation to the literature (Table S1.1).

River basins, and Southeast Asia; as well as in vast areas of North America, Europe, and Southern Asia, especially for soybean and RCG. Jatropha is the only feedstock with all negative DLUC factors (<-4.3 gCO_2/MJ) below the median. There are few compliant pixels (0.7%) with values below -50 gCO_2/MJ, all found in tropical regions with limited carbon stocks in vegetation and yields <2t/ha, where jatropha production generates net SOC gains (Figure S2.2). This is also observed in dry temperate latitudes, through living biomass, where jatropha production is only viable with irrigation (Figure S2.3). Jatropha has negative DLUC values in more than 55% of the CORSIA-compliant pixels, followed by miscanthus (42%) and switchgrass (14%). The latter two also show negative DLUC in the first decile of the distribution of compliant DLUC values (Table S2.1). On the contrary, RCG, maize, and soybean mostly have positive DLUC values (>97% of CORSIA-compliant areas), hence delivering higher mean DLUC factors, i.e., 31.9 gCO_2/MJ for soybean vs. 3.6 gCO_2/MJ for jatropha.

When core-LCA emissions are included, the share of CORSIA-compliant areas decreases by about half or more for ETJ fuels from maize and RCG, respectively. Both pathways have core-LCA emissions >60 gCO_2eq/MJ, mainly due to the higher fertilizer application intensity compared to the other feedstocks (Table S1.6). Compliant pixels still represent 28% of the eligible areas for RCG-ETJ and 37% for maize-ETJ; excluding large areas across Europe, North America, and Central Asia, as well as in South America and Sub-Saharan Africa in the case of maize-ETJ. Jatropha-HEFA and soybean-HEFA respectively have 36% and 47% of eligible areas compliant with criteria 1.1, largely found in South and Central America (and Southern US), Oceania, and Southern Asia, mainly India; while, for the latter, compliant areas also spread across China, Europe, and North America. Switchgrass-ETJ and miscanthus-ETJ show >65% of eligible areas compliant with criterion 1.1 when including core-LCA emissions. This is related to the lower fertilizer doses compared to RCG-ETJ and maize-ETJ pathways. Among CORSIA-compliant pixels, mean DLUC emissions (gCO_2/MJ) vary from 3.6±31.4 for jatropha to 31.9±20.7 for soybean. Mean life cycle GHG emissions (gCO_2eq/MJ) vary from 37.9±19.8 for jatropha-HEFA and 71.9±4.2 for maize-ETJ (Table S2.1).

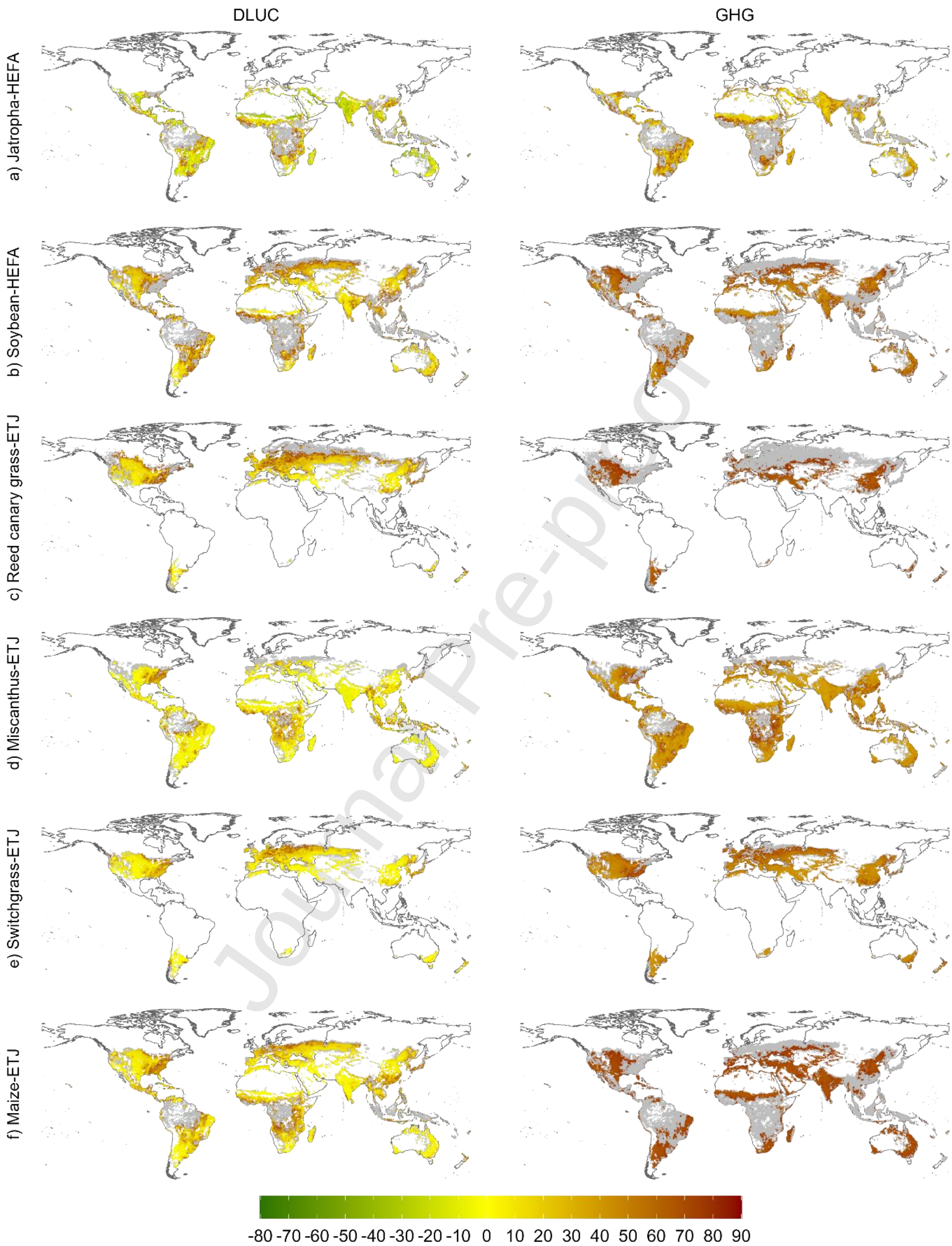

Figure 2. DLUC emission factors and total life cycle GHG emissions (gCO_2eq/MJ) for the jet fuels based on the corresponding feedstocks produced with irrigation, and excluding primary forests, peatland,

wetlands, and protected and biodiversity-rich areas. Only pixels within eligible areas that deliver GHG savings ≥10% are considered, while the rest are greyed out. Pixels with yields <25th percentile (<15th percentiles for switchgrass) are also filtered out. HEFA: hydroprocessed esters and fatty acids; ETJ: ethanol-to-jet.

The results in this section can be used to evaluate criterion 2.2, according to which DLUC values should be used instead of ILUC values to calculate the GHG emission intensity of SAF, when DLUC > ILUC. This requires estimating DLUC factors at the country (global) level, as area-weighted averages considering the respective eligible areas (according to criteria 2.1 and 7.1). Table 1 shows the results for the specific pathways and producing regions covered by CORSIA for the feedstocks of study, based on available core-LCA and ILUC values (ICAO, 2022f). As RCG does not have an accepted ILUC value, DLUC values for several countries are included – all country-average DLUC values are shown in Table S2.2. DLUC emissions per MJ are higher than ILUC values for all pathways, except for maize-ETJ. Most pathways based on perennial grasses or jatropha still meet the GHG reduction criterion 1.1. For miscanthus, exceptions are found in countries with relatively higher average carbon stocks and lower yields. RCG-ETJ's compliance with criterion 1.1 is very sensitive to DLUC, given the relatively high core-LCA value. While DLUC values for cold temperate countries do not deliver sufficient GHG reductions, due to the lower yields and high carbon stocks (especially in soils), RCG-ETJ in drier climates would meet the requirement. However, this pathway would not qualify based on the global average value. When replacing ILUC with DLUC values, soybean-HEFA pathways do not meet the criterion, neither in US, nor in Brazil, nor globally. Despite the lower DLUC factor relative to soybean, maize-ETJ pathways do not meet criterion 1.1, because ILUC values are used in this case. The largest GHG savings (>40%) are quantified for Indian jatropha-HEFA, and switchgrass-ETJ and miscanthus-ETJ in specific countries.

Table 1. Evaluation of compliance with criterion 2.2 by combining country- and global-average DLUC results from this study (for irrigated feedstocks) with accepted ILUC and core-LCA values from CORSIA.

Associated GHG emission reductions (increases) are quantified relative to the CORSIA fossil comparator (89 gCO_2/MJ).

Region	Pathway	CORSIA			This study (Escobar et al.)				
		Core-LCA	ILUC value	Total GHG	Country- and global-average DLUC	DLUC > ILUC	Updated total GHG	GHG reduction (increase)	10% reduction (criteria 1.1)
		gCO_2e/MJ						%	
USA	Soybean oil-HEFA	40.40	24.50	64.90	42.11	YES	82.51	7.3%	NO
Brazil	Soybean oil-HEFA	40.40	27.00	67.40	63.31	YES	103.71	-16.5%	NO
Global	Soybean oil-HEFA	40.40	25.80	66.20	54.20	YES	94.6	-6.3%	NO
India	Jatropha-HEFA	46.90	-24.80	22.10	-10.25	YES	36.65	58.8%	YES
India	Jatropha-HEFA	46.80	-48.10	-1.30	-10.25	YES	36.55	58.9%	YES
USA	Miscanthus-ETJ	43.30	-42.60	0.70	9.99	YES	53.29	40.1%	YES
EU (Croatia)	Miscanthus-ETJ	43.30	-23.30	20.00	39.19	YES	82.49	7.3%	NO
EU (Greece)	Miscanthus-ETJ	43.30	-23.30	20.00	-2.02	YES	41.28	53.6%	YES
EU (Hungary)	Miscanthus-ETJ	43.30	-23.30	20.00	28.31	YES	71.61	19.5%	YES
EU (Italy)	Miscanthus-ETJ	43.30	-23.30	20.00	6.03	YES	49.33	44.6%	YES
EU (Portugal)	Miscanthus-ETJ	43.30	-23.30	20.00	7.89	YES	51.19	42.5%	YES
EU (Romania)	Miscanthus-ETJ	43.30	-23.30	20.00	17.37	YES	60.67	31.8%	YES
EU (Slovenia)	Miscanthus-ETJ	43.30	-23.30	20.00	60.12	YES	103.42	-16.2%	NO
EU (Spain)	Miscanthus-ETJ	43.30	-23.30	20.00	3.09	YES	46.39	47.9%	YES
Global	Miscanthus-ETJ	43.30	-19.00	24.30	6.37	YES	49.67	44.2%	YES
USA	Switchgrass-ETJ	43.90	-10.70	33.20	9.25	YES	53.15	40.3%	YES
Global	Switchgrass-ETJ	43.90	4.80	48.70	11.09	YES	54.99	38.2%	YES
USA	Maize-ETJ	65.70	25.10	90.80	14.59	NO	90.8	-2.0%	NO
Global	Maize-ETJ	65.70	34.90	100.60	18.95	NO	100.6	-13.0%	NO
EU (France)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	25.58	N/A	87.98	1.1%	NO
EU (Germany)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	45.37	N/A	107.77	-21.1%	NO

EU (Greece)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	4.02	N/A	66.42	25.4%	YES
EU (Italy)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	15.58	N/A	77.98	12.4%	YES
EU (Poland)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	40.26	N/A	102.66	-15.3%	NO
EU (Spain)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	13.77	N/A	76.17	14.4%	YES
EU (Sweden)	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	78.33	N/A	140.73	-58.1%	NO
China	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	11.86	N/A	74.26	16.6%	YES
USA	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	19.54	N/A	81.94	7.9%	NO
Canada	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	23.79	N/A	86.19	3.2%	NO
Russian Federation	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	35.81	N/A	98.21	-10.3%	NO
Global	Reed canary grass-ETJ	62.4 (this study)	N/A	62.4	23.94	N/A	86.34	3.0%	NO

3.3. Carbon payback-times and SAF production potentials across CORSIA-compliant areas

DLUC results allow quantifying spatially-explicit CPTs for the analysed SAF production pathways (eq. 8 in the Annex). Figure 3 show positive results across areas compliant with criteria 2.1 and 7.1 (section 3.1). Negative CPTs are greyed out, as these correspond to pixels where there is net carbon sequestration and no GHG emissions to compensate. Jatropha-HEFA and Miscanthus-ETJ show a significant share (~20%) of eligible areas with negative CPTs, corresponding to pixels with negative DLUC factors (Figure 2). Same as DLUC emissions, CPTs are highly variable. Mean CPTs vary from 11.6±14.3 years for switchgrass-ETJ to 54.0±60.0 years for jatropha-HEFA. Only the latter has a mean CPT >50 years. ETJ from switchgrass and miscanthus shows the shortest mean CPTs, followed by maize-ETJ, soybean-HEFA and RCG-ETJ. Most of the estimated CPTs (>60%) for all pathways are <50 years, with nearly 100% for miscanthus-ETJ and switchgrass-ETJ. Only jatropha-HEFA shows CPTs>100 years above the 90th percentile, located in specific pixels around the Amazon and Congo River basins and Southeast Asia (Table S2.1). Some of these pixels can reach CPTs >500 years. After jatropha-HEFA, the longest maximum CPTs are found for maize-ETJ (410.2) and soybean-HEFA (354.1), also in tropical latitudes.

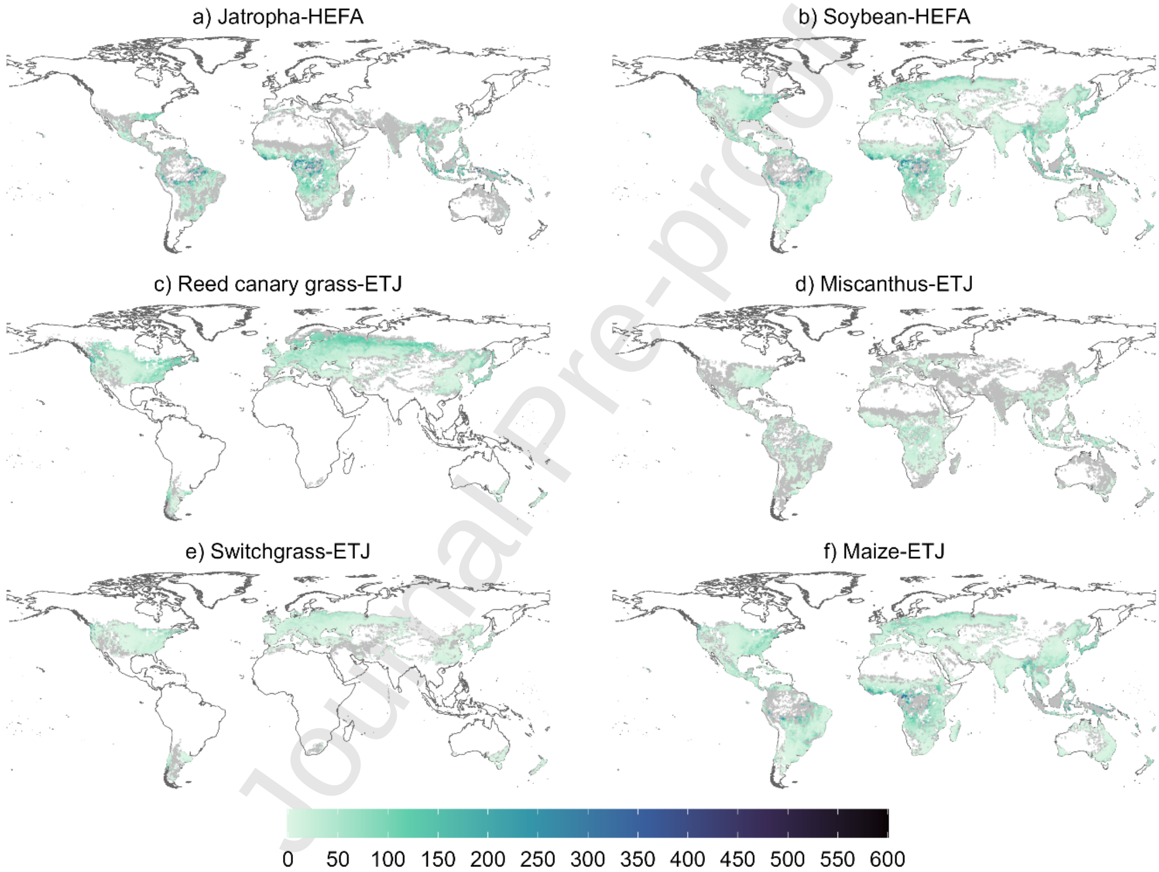

Figure 3. Carbon payback times (years) for the jet fuels produced from irrigated feedstocks, excluding primary forests, peatland, wetlands, and protected and biodiversity-rich areas according to criteria 2.1 and 7.1. Negative results are highlighted in grey, as these correspond to pixels where there is net carbon sequestration, meaning there is no payback time to compensate for GHG emission increases.

Pixels with yields <25^{th} percentile (<15^{th} percentiles for switchgrass) are also greyed out. HEFA: hydroprocessed esters and fatty acids; ETJ: ethanol-to-jet.

Finally, results in section 3.1 and 3.2 are used to estimate maximum production potentials of each feedstock, assuming that cropland (and grassland) areas available in CORSIA-compliant pixels are employed for producing SAF with each feedstock (eq. 9). Global results (PJ) for the scenarios considered are shown in Table 2, as well as the kerosene market share (%). The latter is estimated based on data on global jet fuel kerosene consumption for the year 2019, which represents the all-time high in consumption and is the CORSIA reference year to calculate airlines' emission offsets. This is quantified at 14.4 EJ (404.4 billion litres) considering country-level consumption for both international bunker and domestic aviation (UNSD, 2024). The largest potentials are achieved with irrigated miscanthus (2.94 EJ, 20.4% of 2019 jet fuel consumption) (Table 2), when produced on cropland and grasslands in areas compliant with criteria 2.1 and 7.1, followed by switchgrass (1.55 EJ) and maize (1.47 EJ). The potentials are reduced when implementing criterion 1.1 (2.75 EJ and 1.45 EJ for irrigated miscanthus and switchgrass, respectively, or 6% decrease in potential); especially for soybean, RCG, jatropha, and maize, with a reduction >40%. Soybean, jatropha, and RCG account for 0.2% and 0.8% in the most restrictive scenario (rainfed production in cropland areas compliant with criteria 1.1, 2.1 and 7.1). This is comparable to the current market share of SAF (<0.1%) from all commercial feedstocks (IEA, 2023).

Table 2. SAF production potentials and market share for each feedstock, assuming that these are produced in agricultural land areas compliant with several CORSIA sustainability criteria, both with and without irrigation.

SAF PRODUCTION POTENTIALS (PJ)								
	Cropland areas, in pixels compliant with criteria 2.1 and 7.1 (section 3.1)		Cropland and grassland areas, in pixels compliant with criteria 2.1 and 7.1 (section 3.1)		Cropland areas, in pixels compliant with criteria 1.1, 2.1 and 7.1 (Section 3.2)		Cropland and grassland areas, in pixels compliant with criteria 1.1, 2.1 and 7.1 (Section 3.2)	
	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed

Jatropha	386.2	242.9	520.31	302.39	179.3	114.0	241.3	148.7
Maize	1128.5	730.6	1473.37	891.86	650.9	271.6	872.1	330.2
Miscanthus	2220.7	1282.9	2935.08	1572.99	2055.5	1095.6	2748.1	1360.9
Reed canary grass	769.8	560.4	974.49	671.77	343.6	161.9	472.0	201.9
Soybean	109.3	73.6	141.27	90.16	56.5	24.1	74.3	29.4
Switchgrass	1243.8	787.7	1546.70	913.90	1164.1	698.0	1453.9	810.0
SHARES OVER 2019 AVIATION JET FUEL CONSUMPTION (%)								
	Cropland areas, in pixels compliant with criteria 2.1 and 7.1 (Section 3.1)		Cropland and grassland areas, in pixels compliant with criteria 2.1 and 7.1 (Section 3.1)		Cropland areas, in pixels compliant with criteria 1.1, 2.1 and 7.1 (Section 3.2)		Cropland and grassland areas, in pixels compliant with criteria 1.1, 2.1 and 7.1 (Section 3.2)	
	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed
Jatropha	2.7	1.7	3.6	2.1	1.2	0.8	1.7	1.0
Maize	7.8	5.1	10.2	6.2	4.5	1.9	6.1	2.3
Miscanthus	15.4	8.9	20.4	10.9	14.3	7.6	19.1	9.4
Reed canary grass	5.3	3.9	6.8	4.7	2.4	1.1	3.3	1.4
Soybean	0.8	0.5	1.0	0.6	0.4	0.2	0.5	0.2
Switchgrass	8.6	5.5	10.7	6.3	8.1	4.8	10.1	5.6

4. Discussion

4.1 Limitations of the study

This study implements spatially-explicit data into the IPCC approach (IPCC 2006, 2019) for the estimation of DLUC emissions for SAF production pathways. The IPCC guidelines provide a framework to calculate GHG emissions from land conversion into cropland, taking into account carbon cycle processes among pools at different levels of complexity. Both Tier 1 and 2 introduce spatial variability in carbon stocks (and flows) without the need for data-intensive mechanistic models that simulate biogenic system dynamics as in Tier 3 (Batlle-Aguilar et al., 2011; Goglio et al., 2018; Lugato et al., 2014; Thomas et al., 2013); or to carry out field studies (Achten et al., 2013; Bailis & McCarthy, 2011; Batlle-Bayer et al., 2010). Both mechanistic models or direct field measurements are site-specific and can hardly provide global coverage. The IPCC Tier 1 is frequently applied to include DLUC in LCA studies, by identifying the sourcing regions, associated yields, and land uses being converted in each case (Achten et al., 2010; Malça & Freire, 2012; Shonnard et al., 2015). The influence of these and other assumptions, such as crop management, can be assessed through scenario analysis, defining a discrete number of alternatives (Castanheira et al., 2015; Castanheira & Freire, 2013; Seber et al., 2022). Although the revised guidelines (IPCC, 2019) expand the land conversion possibilities relative to IPCC (2006), mainly in terms of forest age, vegetation carbon stocks are given by default values at a coarse resolution – continental and agroclimatic zone level. Our study provides DLUC estimates at Tier 2 level, capturing spatial variability in global crop yields and carbon stocks in vegetation and soil at a relatively fine resolution.

DLUC estimation follows CORSIA sustainability criteria 2.1 and 2.2 (ICAO, 2022e), assuming that producing SAF feedstock completely clears the existing vegetation in 2010-2015 (Jung et al. 2021), excluding primary forests and intact ecosystems. Eligible areas yet include some pixels with AGB > 100 tC/ha (with values up to 160.09 tC/ha), mainly found in tropical countries such as Cameroon or Indonesia but also in temperate latitudes (e.g., US, Australia). These values are comparable to those given by IPCC (2019) for secondary forests (older than 20 years), e.g., in Asia (tropical rainforest: 131.6 tC/ha), North and South America (tropical moist deciduous forest: 131.0 tC/ha; tropical dry forest: 118.9 tC/ha), or Europe (temperate oceanic forest: 153.9 tC/ha). Similarly, SOC data is consistent with IPCC (2019) SOC values in reference soils. For instance, high activity clay soils in tropical moist climates, such as those found in Brazil, have around 40 tC/ha (top 30 cm) in IPCC (2019), while the country-average SOC content for eligible areas for jatropha and miscanthus in Brazil is 40.8 tC/ha. The default SOC content in high activity clay soils in warm temperate dry climates is 24 tC/ha, e.g., in line with the country-average for RCG grown in Greece (28.3 tC/ha). One limitation of the carbon stock data used is that it is not land cover-specific, which prevents us from estimating DLUC factors for land transitions e.g., from degraded grasslands or marginal lands into SAF feedstock, which could result in lower DLUC values (Seber et al., 2022).

The method presented uses Tier 1 coefficients to quantify SOC changes through agricultural practices, relative to the reference soil. The same crop management is assumed for the annual (medium input, full tillage) and perennial crops evaluated (medium input, reduced tillage). IPCC Tier 1 coefficients are mapped with agroclimatic zones in GLOBIOM, hence reflecting spatial heterogeneity of SOC impacts.

The distinction in tillage practices is made because perennials need less tillage and maintenance compared to annual crops (Don et al., 2012; Iordan et al., 2023; Winkler et al., 2020). Although some studies highlight the potential of perennial crops to be grown with low input intensity, these mostly correspond to marginal lands, where production is oriented to deliver soil improvements and other environmental benefits (Achten et al., 2013; Scordia et al., 2022; Vera et al., 2021). Medium input application was assumed for all crops to minimize the comparative effect of this assumption, taking into account that attainable yield data from GAEZ v4 correspond to medium-high input intensities (Fischer et al., 2021). Agricultural practices greatly influence both SOC changes and yields, which are key determinants of the GHG performance of bioenergy/biofuel crops (Escobar et al., 2017; Fazio & Monti, 2011; Goglio et al., 2012). Therefore, DLUC values should aim to represent spatial heterogeneity in agricultural practices and input intensity, depending on edapho-climatic characteristics. When estimated with process-based models that simulate soil-plant system dynamics or with field experiments, perennial grasses normally deliver GHG benefits over annual crops, especially when produced at the cost of previous cropland or marginal lands (Dheri et al., 2022; Hillier et al., 2009; Zatta et al., 2014). These benefits vary with the level of input intensity, ranging from SOC losses to gains with increased input application (Don et al., 2012; Nguyen et al., 2017; Ogle et al., 2010). SOC changes also depend on the irrigation regime, which determines the N input application (Iordan et al., 2023). Crop management is subject to temporal variability, as farmers adapt their choices to several factors, including climate, prices, etc. (Bessou et al., 2013; Boone et al., 2016). This challenges the generation of global datasets that cover spatial and temporal variability in crop-specific agricultural practices.

Attainable yields had to be considered as most of the feedstocks assessed are not produced on a large scale (except maize and soybean) and there is no global data on actual yields and harvested areas for each feedstock. GAEZ attainable yields are obtained with simulation models that consider agro-climatic and soil characteristics, water availability, as well as the impacts of climate change on crop productivity and irrigation water requirements under current and future climates (Fischer et al., 2021).

Actual yields may differ from the attainable yields considered, mainly due to differences in the actual areas employed – GAEZ v4 considers current croplands. Actual yields may also differ due to the effect of crop management, which is however difficult to represent consistently at a global level, as indicated above. Still, area-weighted average yields at the country level are in line with those of agri-food commodities in FAOSTAT (FAO, 2024), e.g., 3.10 t/ha and 3.20 t/ha for soybean in Brazil and USA (average 2010-2022), respectively; 10.4 t/ha for maize in the US (see Table S1.7). The same method could be replicated for other crops available in GAEZ v4 that are relevant for CORSIA.

CORSIA-compliant area results in sections 3.1 and 3.2 have been used to estimate SAF production potentials. This constitutes a what-if scenario of maximum potentials to be achieved with each feedstock alone, assuming that it grows in available croplands (and grasslands), while these areas may be in practice used for the production of other crops with higher profitability. The approach is similar to that applied by Vera et al. (2021) and Iordan et al. (2023). However, these studies focus on biofuel/bioenergy potentials from perennial grasses in the EU. Iordan et al. (2023) consider available abandoned croplands and attainable yields from GAEZ v3 (Fischer et al., 2012). Vera et al. (2021) consider areas compliant with the EU Renewable Energy Directive according to the GHG emission savings of the resulting road biofuels, simulating future yields under specific agroclimatic and soil characteristics. Other factors may influence SAF potentials, such as crop production costs, actual land availability and profitability in competition with other uses, cost-competitiveness of SAF vs. conventional kerosene, or other policies and climate targets, which require integrated modelling assessments (Mandley et al., 2020; Popp et al., 2011; Reid et al., 2020).

4.2 Further improvements and considerations

Further work could consider simulating yields for alternative input intensity and tillage scenarios. This could be done with the EPIC-IIASA model (Izaurralde et al., 2012; Williams et al., 1989), provided that it progressively includes all crops in this study and others of interest for CORSIA in the GLOBIOM framework (IIASA-IBF, 2023). The analysis could also include ETJ production from second-harvest maize, which has become an important bioenergy feedstock in Brazil (Eckert et al., 2018), normally grown in rotation with soybean (Moreira et al., 2020; Spera et al., 2014). Including second-harvest maize would require data on cropping frequencies, double-cropped areas, and underlying crop rotations on a global scale. GAEZ v4 only includes attainable yield information for single-cropped maize, while CORSIA does not provide core-LCA or ILUC values for second-harvest maize. Second-harvest maize would also have implications for the DLUC factors of soybean produced in Brazil, as this would imply further allocation of emissions among all crops in the rotation (Escobar et al. 2020).

The estimation of DLUC factors assumes an average value for carbon sequestration in living biomass, whereas it should vary with yield. A similar approach was used by WWF & IIASA (2019) to examine SAF production potentials in Sub-Saharan Africa under sustainability constraints. The authors consider different values for living biomass in perennial feedstocks only, depending on the agroclimatic zone, e.g., between 14.9 tC/ha and 17.9 tC/ha for miscanthus. Bailis & Baka (2010) defined different scenarios for carbon sequestration in jatropha in Brazil depending on the fertilization doses and associated yields: e.g., carbon sequestration jatropha ranges from 11 to 20 tC/ha with yields of 1.8 t/ha and 5.35 t/ha, respectively. Achten et al. (2013) consider low (12 tC/ha), medium (17.8 tC/ha), and high (21.4 tC/ha) scenarios for the average living biomass in a 20-year jatropha plantation in (semi)arid areas. Applying the same approach would entail additional assumptions to define different carbon sequestration levels in line with yields, since both depend on the plantation age. In the absence of empirical evidence, we tried to represent conservative carbon sequestration scenarios per feedstock not to benefit the GHG balance, e.g., 12.4 tC/ha in miscanthus; 12.0 tC/ha for jatropha. Although these values do not capture the expected variability of living biomass, they are aligned with the area-weighted global yields (Table S1.1 in ESM), i.e., 2.5 t/ha for irrigated jatropha or 17.3 t/ha for irrigated miscanthus. It must be noted that GAEZ v4 is optimistic as for attainable yields of switchgrass in current cropland compared to the literature surveyed, but this is because the latter mostly covers switchgrass produced in marginal or poorly productive land (Table S1.2). In any case, these calculations ignore the temporal asymmetry between emissions from vegetation loss and uptake by crop re-growth (Cherubini et al., 2016). Further improvements should capture the relation between crop management, irrigation regime, yields, living biomass, and SOC changes.

The results underline that location is decisive for the DLUC emission intensity of SAFs, justifying the need for higher tiers than IPCC Tier 1 to conveniently capture spatial variability in DLUC. The production site determines the existing land uses, carbon stocks, and yields. Our analysis distinguishes between irrigated and rainfed production, determining the attainable yields and the extension of suitability areas. Although attainable yields are only available for locations in which production is agronomically feasible, also considering water availability, the estimation of DLUC as gCO_2/MJ excludes pixels with yields below the first quartile (15^{th} percentile for switchgrass) to represent those locations where production may not be financially viable. Water scarcity can pose further environmental impacts (Liu et al., 2017; Schmitt et al., 2022; WWF & IIASA, 2019). Same as DLUC factors in this study, CORSIA core-LCA values do not reflect variability in management systems, even though fertilizer use and tillage play a key role in agricultural emissions (Eliasson et al., 2023; Escobar et al., 2020). Core-LCA emissions of SAFs from rainfed feedstocks should be slightly lower than those from irrigated ones, due to lower energy consumption. Although out of scope, considering the spatial variability of core-LCA would help identify the sourcing regions of low-carbon SAFs. Multiple LCA studies have shown that assumptions associated with DLUC are yet a more important source of uncertainty in life cycle GHG emissions than uncertainty in life cycle inventory data (Capaz et al., 2021; Malça & Freire, 2011; Seber et al., 2022).

While this study focuses on stochastic uncertainty, DLUC estimates are also subject to epistemic uncertainty (Plevin et al., 2010), derived from the parameters and assumptions to represent changes in carbon cycles and implications for carbon stocks (Curtright et al., 2012; Harris et al., 2015; Whitaker et al., 2018). These include the default input intensity and tillage practices that determine the selection of IPCC Tier 1 coefficients, based on which SOC losses are quantified. The influence of crop management assumptions is assessed by defining alternative scenarios vs. the default one: all feedstocks with reduced tillage and low input intensity or all with tillage and high input intensity. The yields are the same as in the default scenario and do not vary with crop management. The 2006 IPCC coefficients were also tested. Mean values across scenarios are shown in Figure S2.5 in the ESM. On the one hand, low input application increases the DLUC1 factors of both perennial and annual crops, as it decreases carbon gains both with 2006 and 2019 coefficients. The effect of fertilization on SOC is not fully understood, yet this captures how chemical fertilizers enhance soil quality and SOC stability (Han et al., 2016; Mahal et al., 2019; Zhou et al., 2022). On the other hand, reduced tillage tends to lower DLUC1 factors of annual crops, relative to the default scenario, as it reduces tillage-induced N mineralization (Feng et al., 2018). Reduced tillage could lead to increased N_2O emissions through decreased soil aeration and higher soil moisture contents (Don et al., 2012). The 2019 IPCC coefficients reflect how reduced tillage can decrease SOC in dry climates, in contrast to 2006 coefficients that lead to SOC increases in all climates. Furthermore, 2019 coefficients consider that perennial production reduces SOC in polar and temperate latitudes, regardless the crop management, while the 2006 Flu coefficient had no effect on SOC. The updated 2019 Flu coefficients probably reflect the more variable and context-dependent effect that perennial crops have on SOC (Ledo et al., 2020; Qin et al., 2016; van Straaten et al., 2015). This is why DLUC1 decreases for perennial crops with IPCC 2006 coefficients, especially for those crops with large eligible areas in temperate climates (miscanthus, RCG or switchgrass). These differences highlight the importance of understanding the effect of agricultural practices on SOC to decrease GHG emissions of SAFs relative to fossil kerosene (Kent et al., 2020; Qin et al., 2018). Other important assumptions are the reference soil and land uses considered as baseline, and the amortization period. The latter is arbitrarily defined by CORSIA, implying a linear variation of emissions in the years following conversion, which however take place as a one-time effect (Fabbri et al., 2023; Maciel et al., 2022). For SOC decreases, the rate of change is highest during the first years; while for SOC increases, the rate of accumulation tends to follow a sigmoidal curve (IPCC, 2006).

The results can be compared to those from previous studies. Vera et al. (2021) quantify mean DLUC emissions below zero for ethanol from miscanthus, switchgrass, and RCG in the EU, considering spatially-explicit biomass productivities in marginal land. Our DLUC results show wider variability and positive mean values for the three crops (Table S2.1), with the highest DLUC for RCG (27.2 gCO_2eq/MJ). The maximum biomass potential of lignocellulosic energy crops in EU varies between 1.95 EJ/year in 2030 and 2.27 EJ/year in 2050. Iordan et al. (2023) find miscanthus, switchgrass, and RCG promising feedstocks for EU bioenergy production, with bioenergy potentials between 1 and 7 EJ/year. Under rainfed conditions, switchgrass has the largest supply potential (174 Mt/year), while miscanthus has the lowest life cycle GHG emissions (169 $kgCO_2eq/t$ or 1.5 tCO_2eq/ha). Production of all grasses under rainfed conditions leads to net negative GHG emissions through SOC increases in abandoned croplands. With irrigation, annual GHG emissions turn positive for switchgrass and RCG, mostly due to the additional energy required to secure productivity in marginal lands. The effect of irrigation on SOC is however minor, and their estimated SOC changes are in the same range as the ones in this study (Figure S2.2). In terms of CPTs, Elshout et al. (2015) find longer values for maize and soybean, with large areas with CPTs>500 years, mainly because they considered natural (intact) vegetation conversion. Replacing no-input farming with high-input farming tends to shorten the CPTs, by more than 100 years. We only found CPTs >500 years in few pixels in the tropics, with most values <100 years. Elshout et al. (2015) also included N_2O emissions from soil mineralization and (de)nitrification, as well as N_2O from fertilizer application. Gibbs et al. (2008) find higher CPTs and wider variability depending on the land uses converted, including natural vegetation, e.g., between 300-1500 years for maize produced on deforested land. Conversion of grasslands, pastures and existing croplands for biofuel feedstock production yields much shorter CPTs (<100 years); and using marginal lands may generate trade-offs through more energy-intensive management to remain productive.

5. Conclusions

This study provides spatially-explicit estimates at 0.5-degree resolution of DLUC factors, CPTs and SAF production potentials for six CORSIA feedstocks. DLUC emissions originate from the clearing of observed vegetation to produce the crop, excluding primary forests and biodiversity-rich land uses according to CORSIA sustainability criteria 2.1 and 7.1. The analysis represents a what-if scenario in which observed vegetation in CORSIA-eligible land uses is replaced by SAF feedstock. GHG emissions (removals) are estimated at IPCC Tier 2 level as the difference in carbon stocks across pools (soil, vegetation, living biomass) relative to previous uses, using spatially-explicit data and regionalized information on attainable crop yields, land uses converted and underlying carbon stocks. DLUC estimates indicate where producing these specific SAF feedstocks could be counterproductive in terms of GHG savings, reflecting spatial variability in biophysical processes determined by local conditions (e.g., rainfall, soil, and slope characteristics). The irrigation regime translates into differences in yields and the extension of each crop's suitable areas, which vary in terms of initial SOC and vegetation. The results are used to assess compliance with criteria 1.1 and 2.2, i.e., to identify those locations where SAFs would deliver reductions in life cycle GHG emissions of 10%, relative to fossil kerosene, and assess if DLUC > ILUC at the country level., while further market-mediated land use changes are not considered.

The production location is critical for the SAF's GHG emission intensity, and considering only a mean DLUC factor at the country or global levels to identify CORSIA eligible feedstocks can be misleading. Maximum DLUC factors are found across the tropics for those feedstocks that grow in tropical (subtropical) latitudes, where emissions from vegetation loss make the largest share of absolute DLUC emissions. Sustainability criterion 2.1 effectively excludes the most carbon-rich land uses but still includes relatively carbon-rich ones, not categorized as primary forests. When applying criterion 1.1 (10% GHG reduction) to DLUC emissions and excluding non-compliant pixels, soybean SAF shows the highest mean DLUC factor (gCO_2/MJ) (31.9±20.7), followed by RCG (27.2±21.6). Jatropha SAF shows the lowest mean DLUC factor (3.6±31.4), followed by miscanthus (9.2±18.6) and switchgrass (14.5±17.4). When including core-LCA emissions, miscanthus-ETJ and switchgrass-ETJ keep more than 65% of the eligible areas under criteria 2.1 also compliant with criterion 1.1. This percentage is lower for RCG-ETJ (28%), jatropha-HEFA (36%), maize-ETJ (37%), and soybean-HEFA (47%). The sensitivity analysis shows that crop management assumptions are key to quantifying DLUC emissions under the

IPCC approach. Thus, critical aspects remain, such as considering spatial variability in agricultural practices, living biomass, crop rotations or the extent of abandoned and unused land, on which global data is scarce.

When comparing DLUC with CORSIA's ILUC values, most pathways based on perennial grasses or jatropha still meet the 10% reduction criterion 1.1, with some exceptions, mainly for RCG. Country-average DLUC values are higher than ILUC ones for all pathways except for maize, emphasizing the need to provide accepted DLUC values and more specific calculation guidelines for CORSIA, with the challenge of not overlooking variability. Other pathways based on agricultural residues, used cooking oil, and tallow are assumed to have no ILUC/DLUC implications. ILUC modelling usually considers agricultural area savings associated with co-product generation under consequential approaches, especially when these replace crop production for animal feed, such as in maize- and soybean-based SAF pathways. By definition, DLUC estimation excludes these substitution effects through allocation. The four perennial feedstocks assessed bear potential to mitigate GHG emissions from international aviation according to CORSIA sustainability criteria, provided that these are produced in areas where yields are sufficiently high. Irrigated miscanthus provides the highest SAF production potential across CORSIA-compliant areas (2.75 EJ), followed by switchgrass (1.45 EJ), and maize (0.87 EJ), although this depends on the land uses assumed to be available for conversion (cropland and/or grassland). Collective action from policymakers, industry, and investors is needed to ensure SAFs are produced in sites that deliver low DLUC emissions, while overcoming other economic and technological barriers to scale up SAF production and use. Beyond CORSIA, quantifying other environmental impacts is desirable to understand sustainability trade-offs and challenges for SAF promotion, for instance, related to irrigation water demand and scarcity, which can limit production potentials further.

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Annex

- Equations for DLUC emission estimation under the IPCC Tier 1 approach.

$\Delta C = C_{LU_1} - C_{LU_0}$ (eq. 1)

$C_{LU_0} = C_{AGB_0} + C_{BGB_0} + C_{DW_0} + C_{LI\,0} + C_{SOC\,0} + C_{HPW_0}$ (eq. 2)

$C_{LU_1} = C_{AGB_1} + C_{BGB_1} + C_{SOC_1}$ (eq. 3)

$C_{SOC\,0} = C_{REF}$ (eq. 4)

$C_{SOC\,1} = C_{REF} \times F_{LU} \times F_{MG} \times F_I$ (eq. 5)

Where,

ΔC (t/ha): carbon losses (gains) from on-site (direct) land conversion into SAF feedstock production

C_{LU0} (t/ha): total carbon stocks in land uses prior SAF feedstock production

C_{LU1} (t/ha): total carbon stocks in land converted into SAF feedstock production

C_{AGB0} (t/ha): carbon stocks in aboveground biomass (AGB) before land conversion

C_{BGB0} (t/ha): carbon stocks in belowground biomass (BGB) before land conversion

C_{DW0} (t/ha): carbon stocks in dead wood before land conversion

C_{LI0} (t/ha): carbon stocks in litter before land conversion

C_{SOC0} (t/ha): soil organic carbon (SOC) in mineral soils before land conversion

C_{HWP0} (t/ha): carbon stocks in harvested wood products before land conversion; assumed to be zero in Tier 1

C_{AGB1} (t/ha): carbon stocks in AGB after land conversion

C_{BGB1} (t/ha): carbon stocks in BGB after land conversion

C_{SOC1} (t/ha): SOC in mineral soils after land conversion

C_{REF} (t/ha): SOC in reference mineral soils

F_{LU} (dimensionless): Land use coefficient

F_{MG} (dimensionless): Land management coefficient

F_{I} (dimensionless): Input coefficient

In this study, ΔC (tC/ha) is calculated per feedstock (f) at the pixel level (i). Note that C_{AGB1} and C_{BGB1} refer to the carbon sequestration in living biomass shown in Table S1.1 (in ESM), which is downscaled but still the same for all pixels inside the land suitability areas for each crop. F_{LU}, F_{MG}, and F_{I} are taken from IPCC Tier 1 default values (IPCC, 2006) assuming the same management and input intensity for each feedstock (depending in whether it is annual or perennial crop), but still vary with the climatic area in which each pixel is located.

- Equations for DLUC emission factor estimation in different units, after energy allocation.

$$DLUC1_{f,i}\ \left(\frac{tCO_2}{ha}\right) = \frac{\Delta C_{f,i}\left(\frac{tC}{ha}\right) \times \frac{44}{12}}{T\ (years)} \times AF1_f \times AF2_f \text{ (eq. 6)}$$

$$DLUC2_{f,i}\ \left(\frac{gCO_2}{MJ}\right) = \frac{DLUC1_{f,i}\left(\frac{tCO_2}{ha}\right)}{Yield_{f,i}\left(\frac{t}{ha}\right) x\ CE1_f\ (\%)\ x\ CE2_f\ (\%)\ x\ LHV\left(\frac{MJ}{kg}\right)} \times 1000 \text{ (eq. 7)}$$

$$CPT_{f,i}\ (years) = \frac{DLUC2_{f,i}\left(\frac{gCO_2}{MJ}\right) \times T\ (years)}{89\left(\frac{gCO_2}{MJ}\right) - coreLCA_f\left(\frac{gCO_2}{MJ}\right)} \text{ (eq. 8)}$$

$$Potential_{f,i,s}\ (PJ) = \ Area_{f,i,s}\ (ha)\ x\ Yield_{f,i}\left(\frac{t}{ha}\right)\ x\ CE1_f\ (\%)\ x\ CE2_f\ (\%)\ x\ LHV\ \left(\frac{MJ}{kg}\right)\ x\ 10^{-6}$$

(eq. 9)

Where,

$\Delta C_{f,i}$ (tC/ha): change in carbon stocks in soil, AGB and BGB after land conversion into SAF feedstock (f) production in each pixel (i)

$AF1_f$ (dimensionless): allocation factor to the intermediate product (vegetable oil in HEFA and DDGS or straw in ETJ pathways) – see Table S1.5 in ESM

$AF2_f$ (dimensionless): allocation factor to the jet fuel – see Table S1.5 in ESM

T (years): amortization time, 25 years in CORSIA

LHV (MJ/kg): lower heating value of the jet fuel (44 MJ/kg)

$Yield_{f,i}$ (t/ha): yields of each feedstock (f) in each pixel level (i). Yields are estimated as tonnes of dry biomass for lignocellulosic crops (switchgrass, miscanthus, reed canary grass, maize) and as tonnes of dry seed per ha for oilseed crops (jatropha and soybean).

$CE1_f$ (%): conversion efficiency of feedstock into intermediate product, i.e., kg of refined oil per kg of dry seed in HEFA (after extraction losses) and kg ethanol per kg of dry biomass in ETJ pathways – see Table S1.4 in ESM

$CE2_f$ (%): conversion efficiency of intermediate product into jet fuel, as kg of jet fuel per kg of refined oil in HEFA pathways or per kg of ethanol in ETJ pathways – see Table S1.4 in ESM

$CPT_{f,i}$ (years): carbon payback time for of each feedstock (f) in each pixel level (i)

$CoreLCA_f$ emissions (gCO_2eq/MJ): core-LCA emissions from well to wake, for SAF from each feedstock (f); these are both pathway- and feedstock-specific

$Area_{f,i,s}$ (ha): pixels (i) for producing SAF from each feedstock (f) in each scenario (s): compliant with criteria 2.1 and 7.1; also compliant with criteria 1.1

$Potential_{f,i,s}$ (PJ): production potential for SAF based on each feedstock (f) in each pixel level (i), in each scenario (s): compliant with criteria 2.1 and 7.1; also compliant with criteria 1.1.

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- Study provides spatially-explicit (50x50 km) direct LUC emissions of aviation fuels
- DLUC emissions arise from carbon stock changes in soil and biomass at IPCC Tier 2
- Results show CORSIA-compliant areas, C payback times and SAF potentials for 6 crops
- Soy jet fuel has the highest mean DLUC factor (gCO_2/MJ) and jatropha the lowest
- Miscanthus, switchgrass and jatropha show large areas where jet fuel decreases GHG