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Greenhouse gas emission curves for advanced biofuel supply chains

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Most climate change mitigation scenarios that are consistent with the 1.5–2 °C target rely on a large-scale contribution from biomass, including advanced (second-generation) biofuels. However, land-based biofuel production has been associated with substantial land-use change emissions. Previous studies show a wide range of emission factors, often hiding the influence of spatial heterogeneity. Here we introduce a spatially explicit method for assessing the supply of advanced biofuels at different emission factors and present the results as emission curves. Dedicated crops grown on grasslands, savannahs and abandoned agricultural lands could provide 30 $EJ_{Biofuel}\,yr^{-1}$ with emission factors less than 40 kg of CO_2-equivalent (CO_2e) emissions per $GJ_{Biofuel}$ (for an 85-year time horizon). This increases to 100 $EJ_{Biofuel}\,yr^{-1}$ for emission factors less than 60 $kgCO_2e\,GJ_{Biofuel}^{-1}$. While these results are uncertain and depend on model assumptions (including time horizon, spatial resolution, technology assumptions and so on), emission curves improve our understanding of the relationship between biofuel supply and its potential contribution to climate change mitigation while accounting for spatial heterogeneity.

Meeting the greenhouse gas (GHG) emission reduction targets that are currently discussed for international climate policy will require the energy system to have net zero emissions[1,2]. Mitigation scenarios, which are used to explore how this can be achieved, often show a substantial contribution from bioenergy, especially as a fuel in the transport sector or as a feedstock for power production (possibly in combination with carbon capture and storage)[3–6]. Policies to promote the use of biofuels through blending targets and support schemes for fuels are already in place in Europe and the United States, as well as other countries around the world[7]. However, bioenergy production (with the exception of residues) is associated with land-use change (LUC), which leads to changes in both above- and belowground carbon stocks and consequent emissions[8]. These have major consequences for the effectiveness of GHG emissions reductions, while LUC could also have negative implications for biodiversity and food production[9–12]. In addition, there are further emissions associated with fertilizer and non-renewable energy use in the production of bioenergy[13].

The emissions associated with bioenergy production can be expressed in terms of the ratio of GHG emissions per unit of bioenergy produced, called the emission factor (EF). These emission factors can be compared with the avoided emissions from using a unit of bioenergy in the energy system, providing a useful framework for evaluating bioenergy policies. Studies have looked into LUC emissions of bioenergy supply by, for example, investigating specific supply chains or using equilibrium models to project market-mediated LUC emissions[13–17]. Yet there is little consensus among studies with EFs ranging from negative values to values larger than 100 $kgCO_2e\,GJ_{Biofuel}^{-1}$ (ref. [18]). These discrepancies are caused by the large uncertainty and variation of key parameters such as crop yields, carbon stocks and projected LUC[19]. A key reason for this variation is spatial heterogeneity[20–22]. As a result, the potential supply of advanced biofuels and how this may change for different GHG emission constraints, as well as which LUC would provide the best possibilities for advanced biofuels as a climate mitigation strategy, are still important knowledge gaps. Here, we develop and apply a spatially explicit method for determining and presenting long-term EFs for biofuels that allows for a better representation of the underlying heterogeneity. By explicitly accounting for the spatial heterogeneity, our approach can also explain part of the EF range reported in the literature. Furthermore, we discuss the effects of different definitions of the break-even point and scenario assumptions on calculating the payback period (PBP), defined as the number of years before GHG savings from displacing fossil fuels outweigh the emissions from biofuel production, in the Supplementary Information[16,20,21,23].

Since advanced biofuels often constitute a major component of bioenergy use in climate mitigation scenarios, we focus our analysis on the production of lignocellulosic methanol from grass or wood and sugarcane ethanol. We highlight the potential supply of these advanced biofuels at increasing EF levels, hereafter called emission curves. These curves show how GHG emissions change when biofuels are increasingly produced on (from a GHG perspective) less suitable lands, that is, those with rising EFs. This goes beyond existing research by providing insight into both the spatial heterogeneity of biofuel GHG characteristics and the potential supply of advanced biofuels at given emission constraints.

Biofuel crops can be produced either on land that is now in use for food or feed crop (thus displacing agricultural production leading to indirect LUC (ILUC) elsewhere), or on natural or abandoned lands. The results presented here apply only to the latter case, focusing only where direct LUC is relevant.

Spatial variation

Maps of the instantaneous and gradual components of the EF for an 85-yr time horizon (EF_{85}) are shown in Fig. 1. The emissions from non-renewable energy use in biomass production and biofuel conversion (approximately 20 $kgCO_2\,GJ_{Biofuel}^{-1}$) are not explicitly shown

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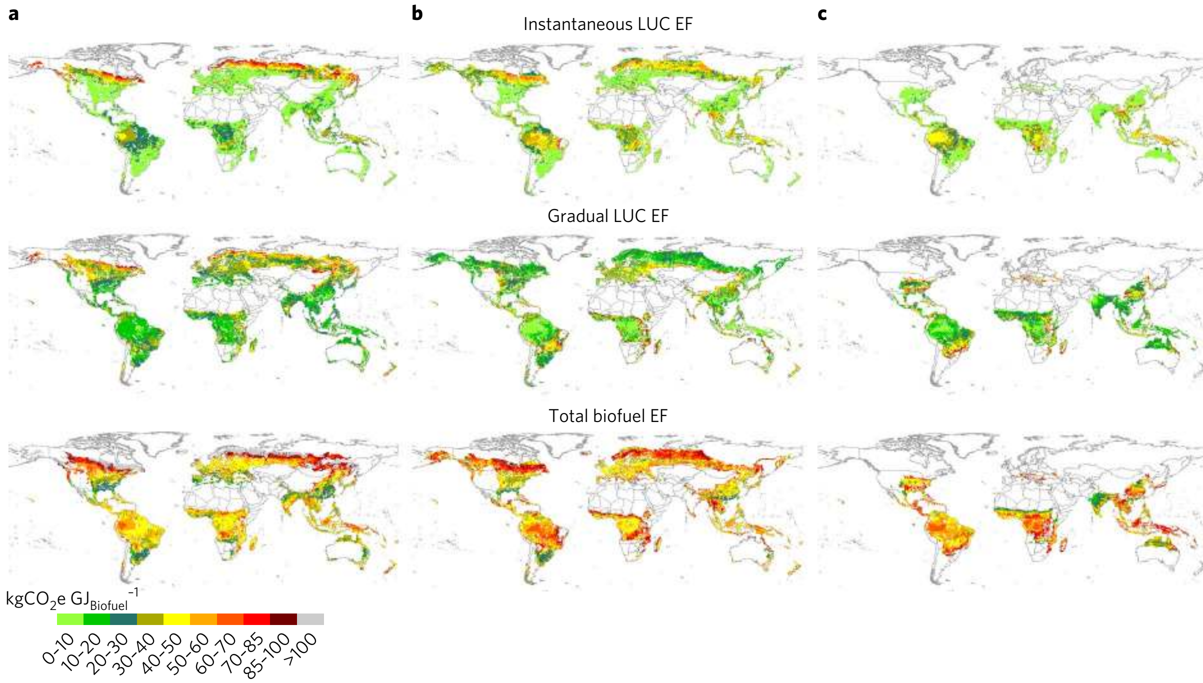

Fig. 1 | Maps of EF_{85} and its components. a, Grass methanol. **b**, Wood methanol. **c**, Sugarcane ethanol. The top row shows the instantaneous emissions due to land clearing, gradual emissions (2016–2100) are shown in the middle row and total emissions on the bottom row. Conversion emissions (~20 $kgCO_2\,GJ_{Biofuel}^{-1}$) are not shown separately, but are included in the total EF_{85}. These maps include current and projected agricultural lands that are excluded in all other figures and quoted results.

but are included in the Total (bottom row of Fig. 1). In most cases carbon stock changes subsequent to the initial LUC (that is, gradual emissions) are a sizeable fraction of the EF_{85}. Gradual emissions are most important in boreal forests, grasslands and savannahs where they may contribute up to 50% of the final EF_{85}.

The mean EF_{85} and 10th–90th percentile range are 72(37–127), 59(37–81) and 58(33–78) $kgCO_2e\,GJ_{Biofuel}^{-1}$ for grass methanol, wood methanol and sugarcane ethanol, respectively. For comparison, the EF of gasoline is 87 $kgCO_2e\,GJ^{-1}$. The large spread in EF_{85} is due to spatial variations in the initial and projected carbon stocks and differences in crop yields. The lowest mean EF_{85} is observed on grasslands at 45(20–71), 51(18–80) and 36(24–50) $kgCO_2e\,GJ_{Biofuel}^{-1}$ for grass methanol, wood methanol and sugarcane ethanol, respectively. Furthermore, due to their high productivity, EFs below 60 $kgCO_2e\,GJ_{Biofuel}^{-1}$ can also be achieved on agricultural lands that are projected to be abandoned in this land scenario, with grass methanol exhibiting the lowest values at 47(30–65) $kgCO_2e\,GJ_{Biofuel}^{-1}$. These results assume a single biofuel type being produced globally to contrast differences across feedstocks. If the best performing biofuel—from an EF_{85} perspective—was produced in each grid cell, the global mean EF_{85} would be 45(16–74) $kgCO_2e\,GJ_{Biofuel}^{-1}$. The extremely large ranges in the 10th–90th percentiles, as well in as the absolute value of EF_{85}, indicate that only part of the lands, even within specific biomes, can provide biofuels with appreciable climate mitigation benefits within the twenty-first century.

Biofuel supply and corresponding emissions

The high variability in EF_{85} indicates that spatial heterogeneity needs to be taken into account when assessing the climate effects of biofuel production. While spatial patterns of EFs effectively illustrate the high variance of the biofuel EF_{85}, they require further aggregation to assess biofuel potentials at any given emission rate. Fig. 2 presents emission curves that show the potential of each biofuel with increasing EF_{85}, highlighting the relationship between biofuel potential and the corresponding emission rate. The curves have been disaggregated across five biomes: savannahs, natural grasslands, temperate, tropical and boreal forests. Agricultural lands that are projected to be abandoned in the selected land scenario are also included.

Globally, there is a very large potential from all feedstocks (in excess of 300 $EJ_{Biofuel}\,yr^{-1}$) for biofuels, with the largest contribution coming from tropical biomes. This large potential can only be achieved if biofuel production without any constraints is assumed, that is, even in lands with very poor GHG performance. Almost 90% of this ultimate potential is only available at an EF_{85} above 40 $kgCO_2e\,GJ_{Biofuel}^{-1}$ and is thus not useable in a meaningful way for climate change mitigation within the twenty-first century, especially when also considering that rebound effects can further reduce mitigation effectiveness (see Supplementary Information). A potential of 22–65 $EJ_{Biofuel}\,yr^{-1}$ would meet a criterion of being below 40 $kgCO_2e\,GJ_{Biofuel}^{-1}$ (for comparison, a recent study estimated that 100 $EJ_{Primary}$ of bioenergy are available with high agreement among experts, based on a wider set of sustainability criteria[24]). The emission curves highlight that even though natural grasslands have the lowest mean EF_{85}, the potential in these lands is less than 5 $EJ_{Biofuel}\,yr^{-1}$ due to the limited area of this biome and the relatively low yields. When comparing the three supply chains, it can be seen that although sugarcane ethanol has a better EF_{85} on average, it has a lower biofuel production potential at any given emission level than grass- and wood-based biofuels. This is because the latter two can be grown in more locations than sugarcane (Fig. 1). An overview of numerical results is available in the Supplementary Information.

Using a PBP_{GHG} criterion of less than 20 years, as used by policies (see further discussion below), and assuming no rebound effect, the potentials of grass methanol, wood methanol and sugarcane ethanol are 31 $EJ_{Biofuel}\,yr^{-1}$ 12 $EJ_{Biofuel}\,yr^{-1}$ and 16 $EJ_{Biofuel}\,yr^{-1}$ respectively. These numbers increase to 264 $EJ_{Biofuel}\,yr^{-1}$, 131 $EJ_{Biofuel}\,yr^{-1}$ and 58 $EJ_{Biofuel}\,yr^{-1}$ if the PBP_{GHG} is increased to 50 years. Assuming

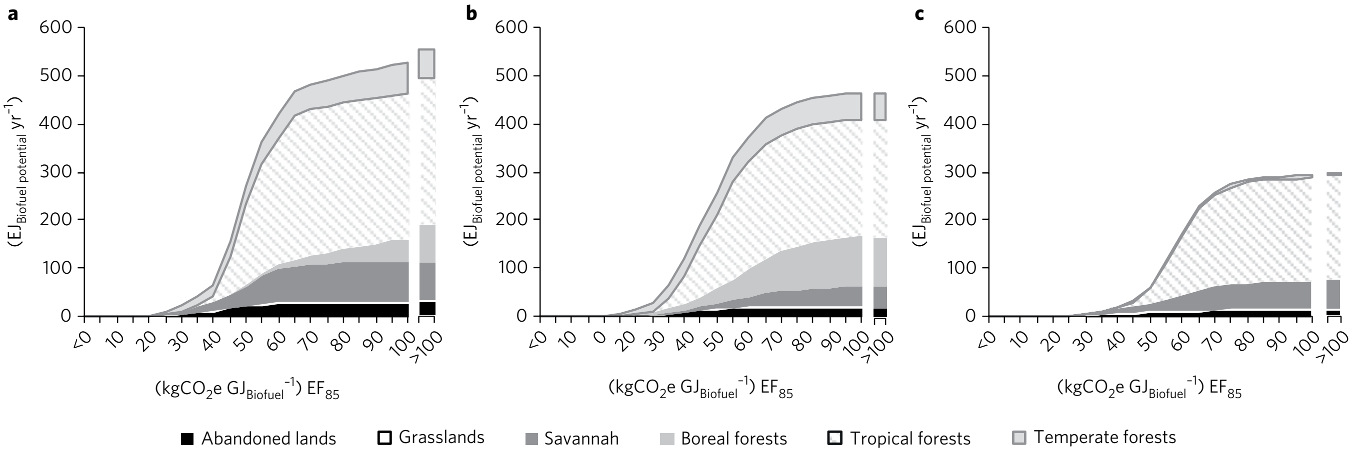

Fig. 2 | EF_{85} emission curves disaggregated for different initial land-cover types. a, Grass methanol. **b**, Wood methanol. **c**, Sugarcane ethanol. The last column of each panel shows the maximum potential for each biofuel. The curves account for the projected changes in crop yield; these curves cannot be summed as the projected land changes are limited to a single biofuel type.

production of the best performing biofuel—from an EF_{85} perspective—in each grid-cell, the potentials would be 41 $EJ_{Biofuel}\,yr^{-1}$ and 298 $EJ_{Biofuel}\,yr^{-1}$ for PBP_{GHG} criteria of 20 and 50 years, respectively (see the Supplementary Information for a discussion on different PBP accounting methods).

Importance and interpretation of uncertainties

Fig. 3 shows the importance of various uncertainties for the emission curve calculations. The sensitivity of the results to technological assumptions indicates that improvements in the conversion technologies and crop yields are a prerequisite for low-GHG biofuels: no improvements in conversion and crop yields results in reduced potentials, especially at a low EF_{85}. In our method, the assumed exclusion of agricultural lands relates directly to uncertainties in the future development of agricultural demand. The default projection assumes that approximately 300 Mha are abandoned by 2100, while a more optimistic land-use projection leads to land availability from abandoned agricultural land increasing to 1,000 Mha. As abandoned agricultural lands tend to be more productive, the biofuel potential at a low EF_{85} is boosted in this case. The use of more agricultural area for bioenergy production could also be achieved by increased yields induced by bioenergy demand, something which is not specifically investigated here. Assumptions about climate projections and the underlying atmospheric CO_2 concentration pathways also affect the results due to changing productivities of natural and agricultural plants. The impact can only partly be studied: similar to most crop models, the crop representation in IMAGE-LPJmL does not account for extreme weather events, but responds reasonably well to high temperature exposure[25]. Moreover, it should be noted that the gains from CO_2 fertilization are uncertain, and possibly overestimated in current crop models[26–28]. Thus, we have excluded the CO_2 fertilization effects in the the sensitivity projection from IPCC Representative Concentration Pathway 6.0 (RCP6.0). The overall potential, as well as the volume of biofuels available at an EF_{85} of less than 40 $kgCO_2e\,GJ_{Biofuel}^{-1}$, for RCP 6.0 shows a slight decrease due to yield losses driven by increasing global temperatures and the prevalence of droughts[29–31]. These effects could be partly mitigated

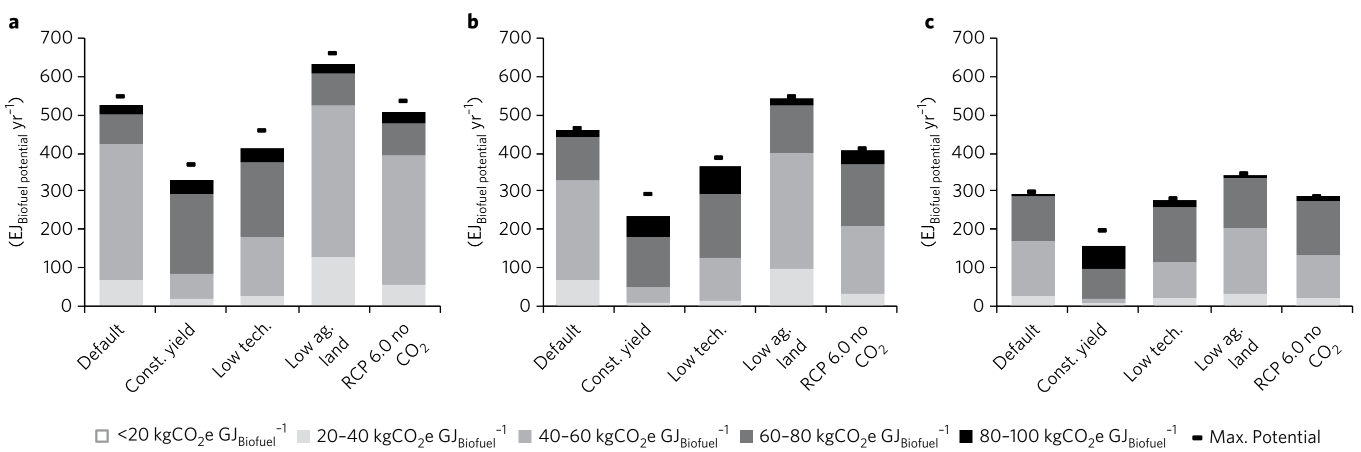

Fig. 3 | Effect of assumptions on potential at different EF_{85} values. Each assumption is tested independently. **a**, Grass methanol. **b**, Wood methanol. **c**, Sugarcane ethanol. Const. yield indicates that the yields are kept constant at 2015 levels. Low tech. is used to denote pessimistic projections on biofuel conversion technological development. Low ag. land indicates the land availability based on a land scenario with increased agricultural abandonment. RCP 6.0 no CO_2 indicates that climate projections with a radiative forcing in 2100 of 6.0 W m^{-2}, not accounting for the effects of CO_2 fertilization, were used. Numerical results and the underlying assumptions are available in the Supplementary Information.

by adaptation measures such as improved cultivars and different management practices[26,32,33].

One explicit assumption of our method is that the carbon content of the original natural vegetation cleared before biofuel production is emitted with no energy production. Determining the energy potential of the original natural vegetation is difficult due to uncertainties in its quality. However, first-order estimates (see the Supplementary Information) lead to decreases in EFs of 10–15%.

Fig. 3 only reflects the parametric uncertainty in a relatively small fraction of the parameters in IMAGE-LPJmL. Comparisons of Global Gridded Crop Models (GGCMs) have highlighted uncertainties in the representation of carbon and nitrogen cycles, yield variability and the effects of climate change. In these comparisons LPJmL is consistently well within the ranges presented[30,34–36]. Still other uncertainties involve the impact of climate variability on land use that is normally not accounted for in crop models, for instance. Parametric, scenario and model uncertainties should be further explored to better understand the robustness of our results. In this context, the emission curves produced from other GGCMs and land-use scenarios would provide great insight.

This study focuses only on biofuels, while other uses of biomass for energy purposes (gases, heat and electricity) may lead to very different emission curves. While the EFs would be broadly similar, the PBP_{GHG} for woody and grass-based biomass could be much lower if biomass is used to substitute coal in electricity generators. Additionally, if biofuel or bioelectricity production is combined with carbon capture and storage, further emission reductions could be achieved[37]. In this light, a tax on the carbon content of primary energy carriers could ensure the appropriate allocation of biomass and avoid leakage of replaced fossil fuels[38].

A key uncertainty concerns indirect effects of biofuel production, such as the displacement of agricultural land and consequent ILUC emissions. Economic models have been used to determine ILUC effects, but the results are subject to uncertainties in agricultural expansion, price elasticities and projected LUC[39,40]. Here, land availability is constrained by projections of future agricultural demand, thus the EFs are consistent with future food production, and are based on targeting biofuel production on unused lands (something that is promoted in current biofuel policies[41]). This study evaluates the suitability of different locations from a biophysical perspective. Production on existing agricultural land would displace agriculture onto lands for which we have determined EFs. Consequently, our results provide an indication for where such expansion should be directed to mitigate the effects of ILUC.

Time-horizon selection and relevance for biofuel policies

The selection of a time horizon is a key methodological issue for assessing the GHG implications of biofuel production. However, this choice is inherently arbitrary, with the IPCC and European Union using 20 years, and the US Environmental Protection Agency using 30 years[42–44]. These time horizons have been justified as they reflect the lifespan of typical biofuel production facilities and policies, the uncertainty of future biofuel production and emissions and the difficulties involved in valuing future emissions. Conversely, given that climate mitigation is a long-term goal, it has been argued that a time horizon of up to 100 years may be appropriate[45,46]. The results presented above use an 85 year time horizon (results for a 20 year time horizon are presented in the Supplementary Information), which is consistent with the projections of IMAGE-LPJmL, as this allows for better accounting of the gradual carbon fluxes that form a sizeable portion of the final emission factor (20–30% globally, up to 50% for grasslands and boreal forests). Our 85 year time-horizon implicitly assumes biofuel production and consumption over that period, in agreement with climate change mitigation pathways of integrated assessment models[2,5,6].

Some policies aimed at promoting biofuel use assign specific time horizons, and thus implicitly make judgements on the biofuel volume that can be supplied. The European Renewable Energy Directive (RED) 2009/28/EC[43] requires that GHG savings of biofuels should be at least 35% until 2016, 50% from 2017 to 2018 and 60% thereafter while Annex V of the directive states that biofuel GHG calculations should have a 20 year time horizon. Using the methods developed in this study, we can estimate the biofuel supply—produced only from dedicated energy crops, not from residues—in 2020, 1 $EJ_{Biofuel}\,yr^{-1}$ is globally consistent with this target, increasing to 3 $EJ_{Biofuel}\,yr^{-1}$ by 2050. Using a more optimistic land scenario does not lead to much higher potentials, highlighting that the available locations with such a low EF_{20} are very limited. Instead, if the EF_{85} emission curves were used, the RED conformant biofuel supply would be 31 $EJ_{Biofuel}\,yr^{-1}$ in 2020 (8–30 $EJ_{Biofuel}\,yr^{-1}$ for individual biofuels), increasing to 46 $EJ_{Biofuel}\,yr^{-1}$ in 2050 (12–40 $EJ_{Biofuel}\,yr^{-1}$ for individual biofuels). Note that this is the supply in those particular years and cannot be derived from Fig. 2 where biofuel potentials are presented as 2016–2100 averages. To put these numbers into context, in 2012 the global demand for transport fuels was in the order of 100 EJ yr^{-1} and is projected to approach 150 EJ yr^{-1} by 2050[4]. Consequently, combining a 60% reduction target and the 20 year time horizon in the RED severely limits the potential of biofuels produced from energy crops. Furthermore, the results of this study show that GHG effects of biofuels vary hugely across both locations and source of emissions (instant and gradual LUC and conversion). This heterogeneity creates challenges for successful policies as restrictions and guidelines (on land use, technology, management and so on) have to be precise to be effective.

Future avenues for research

We present a novel method that allows for better quantification of the relationship between spatially heterogeneous biophysical processes and biofuel supply. By presenting biofuel supply in terms of emission curves, this study aims to provide a clearer understanding of biofuel quantities and their climate implications. Furthermore, by tracking the long-term changes in carbon stocks due to biofuel production and natural changes, this study highlights the importance of accounting for both the spatial and temporal aspects of biofuel production, which may lead to more pessimistic results than existing assessments[13,21]. The concept of emission curves provides a transparent tool to contrast the emissions and mitigation potential of biofuels, and to explore the impact of different assumptions and uncertainties across models. The use of such curves could help to evaluate the trade-off between biofuel supply and afforestation possibilities, which would increase biogenic carbon uptake, and could provide further insights for land-use and climate policy[22,47]. However, while we assess the potential of biofuels at different emission levels, the challenge of policy implementation still remains. Without very specific regulations, the production of any of the abovementioned potentials would very probably involve higher emissions. To actually make use of the low-EF locations presented here, production would have to be directed towards low-carbon ecosystems. Recent developments seem to favour direct LUC for biofuel production, as it can be better monitored than highly uncertain ILUC[41]. Furthermore, the method can be combined with biofuel cost estimates as well as other important constraints not explored in this study[48]. Improvements in the understanding of the spatial heterogeneity in water availability, biodiversity, climate change impacts and the effects of bioenergy production on food prices and human well-being, combined with the presented concept of emission curves, could give a better understanding of the sustainable potential of biofuels.

Finally, it is important to note that besides biofuels, biomass can be used for a number of other energy and material processes (electricity, heat and chemicals) and can possibly be combined with carbon capture technologies to achieve so-called negative emissions.

The method introduced here can be used together with bioenergy mitigation curves for various end uses and conversion technologies to better evaluate different biomass use strategies. With such flexibility for user-defined specifications, emission curves can act as a basis for a more constructive discussion of the advantages and disadvantages of different bioenergy uses in terms of their GHG balances.

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Author contributions

V.D., J.C.D, E.S. B.W., A.F. and D.P.v.V developed the methodological framework. J.C.D. conducted the IMAGE-LPJmL model simulations. E.S. and C.M. checked the consistency of carbon stocks and flows in IMAGE-LPJmL. V.D. calculated the EFs and PBPs. All authors contributed to writing the manuscript.

Competing interests

The authors declare no competing financial interests.

Additional information

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Methods

General. We calculate GHG emissions per GJ of biofuel produced for different crops in a geographically explicit way. The information on emissions is subsequently used to derive emission curves (by sorting and summing grid cells in an ascending order). The curves can be compared with the avoided emissions of the fossil fuels that are substituted to biofuels to assess the possible gains of using biofuels. The GHG emissions included in this study are CO_2 and N_2O from LUC, biomass production and non-renewable energy use for conversion of biomass to biofuels. The calculations of the study are done on 30 minute × 30 minute raster maps. The crops/biofuel chains included are grass methanol, wood methanol and sugarcane ethanol. Grass crops are assumed to be *Miscanthus*, and woody crops are willow and eucalyptus for temperate and tropical biomes, respectively.

We use the integrated assessment modelling framework IMAGE[49], which makes use of the fully coupled vegetation, crop and hydrological model LPJmL[50,51]. This framework projects the biofuel potentials and long-term carbon fluxes of LUC while also accounting for other dynamic factors such as the land-use scenario and the impact of climate change. The results assume a median land-use scenario (SSP2) in combination with a 2.6 W m^{-2} radiative forcing climate scenario[19,52–55]. We only evaluate biofuels that are grown on non-agricultural lands, thereby avoiding the uncertainties related to the dynamics of the use of agricultural land, such as the induced displacement of food production and ILUC, and the potential impacts on diets and yields. This is contrary to some earlier work with the IMAGE framework where we—also making use of the coupled MAGNET model—assessed ILUC effects explicitly[56]. Here, we analyse non-agricultural lands for biofuel EFs, to show which potentials exists when just considering direct LUC. The spatially explicit EF values account for emissions along the complete supply chain, including the instantaneous and gradual changes in carbon stocks due to LUC, foregone sequestration, nitrogen from fertilizer application and non-renewable energy use in biofuel production.

Tracking carbon fluxes. Many studies and established methods for assessing biofuel GHG emissions simplify the emissions from LUC[21,42,57,58]. They tend to ignore or simplify carbon fluxes in the years following the initial LUC by assuming static soil carbon stocks in the baseline and ignoring natural vegetation dynamics and land-use history[59,60]. In this study, IMAGE-LPJmL is used to project the development of above- and belowground carbon stocks for two opposing cases for the 2015–2100 time period: natural vegetation (NV) and biofuel profuction (BP).

Natural vegetation. This case assumes no biofuel production. Land cover is either natural vegetation or agricultural land. This case acts as the benchmark with which biofuel production is compared. As mentioned above, the land-use scenario is based on the SSP2 baseline. For agricultural lands that are projected to be abandoned in this scenario, it is assumed that they return to their natural vegetation (regrowth).

Biofuel production. Starting in 2015, natural vegetation or abandoned agricultural lands are replaced by biofuel crops. The only constraint applied is that potential yields should be more than negligible. The aboveground carbon content of biofuel crops is ignored since it is assumed that all produced biofuels are combusted, and belowground carbon thus rebalances according to the new conditions. Climate feedbacks from land clearing are ignored (that is, climate is assumed to be identical to the NV case), but climate effects on yields and carbon stocks follow the RCP2.6 (default) or RCP6.0 (sensitivity) trajectory. The BP case is repeated for the three primary crop types included in this study: grass, wood and sugarcane.These projections are not intended to be realistic scenarios, but rather stylized model results to make the EF and PBP calculations possible. The methodology applied here takes into account future developments of carbon and nitrogen stocks. Thus re-balancing of soil carbon in the BP case and projections of above- and belowground carbon stocks in the NV case are accounted for.

Calculating EFs. All emissions are calculated as the difference in the carbon stocks between NV and BP. Instantaneous emissions are those due to land clearing take place in 2015, while in all following years (2016–2100) the differences in carbon stocks between the two cases form the gradual increase (or decrease) of cumulative emissions. Spatially explicit EFs are calculated by determining the ratio of cumulative biofuel production to cumulative emissions over the 85 year projection period (2015–2100). Consequently, if cumulative production of biofuels increases faster than the cumulative emissions, the EF will decrease over time, highlighting the importance of the time horizon. As explained above, our calculations for the emission factors are based on an 85 year time horizon to better capture the long-term effects of biofuel production and land-based carbon stocks. The PBP_{GHG} is the time required for the EFs to fall (and remain) below that of gasoline, as beyond that point the cumulative emissions from biofuel production are less than the emission savings from gasoline replacement.

Further details of the methods used are available in the Supplementary Information.

Data availability. The following data sets generated during the current study are available online.

The maps of the biofuel EFs (in $kgCO_2e\,GJ_{Biofuel}^{-1}$) for time horizons of 2015 to 2035, 2050, 2075 and 2100 are available at the following websites for grass methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/NWSecEF.nc), wood methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/WSecEF.nc) and sugarcane ethanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/SCSecEF.nc).

The maps of the average annual biofuel potentials (in $GJ_{Biofuel}$) for 2035, 2050, 2075 and 2100 are available at the following websites for grass methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/NWSec.nc), wood methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/WSec.nc) and sugarcane ethanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/SCSec.nc).

The land areas that are potentially available for biofuel production (that is, non-agricultural, non-negligible yield lands) according to the SSP2 baseline for the period 2015–2100 are available at the following websites for grass methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/NWSec.nc), wood methanol (ftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/WLand.nc) and sugarcane ethanol (fftp://ftp.pbl.nl/image/public/biofuel_emission_curves_NCLIM-16071233/SCLand.nc).

The IMAGE projections of the SSP2 scenario used in this analysis can be found on the IMAGE download website (http://themasites.pbl.nl/models/image/index.php/Download).

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