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Spatially-explicit environmental assessment of bioethanol from miscanthus and switchgrass in France

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ABSTRACT

Bioethanol is promoted as a means of tackling climate change, diversifying energy sources and securing energy supply. However, there also concerns that their wider deployment could lead to unintended environmental consequences. Life cycle assessment (LCA) is a widely used methodology to assess the environmental performance of biofuels. However, its outcomes strongly depend on the inventory data and modeling assumptions. Agronomic variables such as crop yields, nitrogen fertilizer rates or field emissions of nitrous oxide are very sensitive inputs, as are soil carbon dynamics in response to land use changes (LUC) entailed by the deployment of energy crops. Models simulating agroecosystem processes and the economics of agricultural farms are promising tools to predict such variables and improve the reliability of LCA.

Here, we combined the agro-ecosystem model CERES-EGC, the farm economic model AROPAj and the LCA approach to investigate the effect of local drivers on the environmental impacts of bioethanol from miscanthus and switchgrass over France.

Overall, lignocellulosic bioethanol achieved GHG abatement targets in the 74 %–94 % range compared to gasoline, and complied with the 50 % minimum imposed by European regulations. Miscanthus-based ethanol achieved up to twice lower environmental impacts than switchgrass due to 50 % higher biomass yields overall. Low fertilizer N input rates (in the 0-30 kg N ha^{-1} yr^{-1} range) proved the most efficient strategy to optimize energy return. Significant inter-regional variability occurred, especially in terms of soil C sequestration rates, which weighed in substantially on GHG budgets. Some regions were more efficient than others as a result, which advocates a site-specific approach and a potential prioritization when planning biorefineries, taking into account local production and environmental performance potentials. Compared to previous studies, ours provided high-resolution data in terms of crop yields, nitrous oxide emissions and soil C dynamics, factoring in LUC effects at local to regional scales.

1. Introduction

At the Paris Conference of Parties in 2015, over 190 nations re-stated the crucial aim of keeping the increase in global average temperature relative to pre-industrial levels under 2 °C, and possibly under 1.5 °C. Following the Paris conference, France drew up a climate policy agenda including the following objectives: increasing the share of renewable energy by 33 % by 2030, reducing greenhouse gas (GHG) emissions by 40 % relative to 1990 by the same year, and achieving carbon neutrality (zero net emissions) by 2050 (MTES, 2020). Bioenergy plays a key role in the energy transition called for by this national plan, in particular for the transport sector with a projected increase in the use of biofuels. Current liquid biofuels, which include bioethanol and biodiesel, are made from sugar and starch-based crops as well as oilseed crops. Sugar beet and cereals (wheat and maize) are the primary feedstocks for bioethanol production in France, but their low GHG savings relative to gasoline combined with competing food and feed markets limit their expansion (Hirani et al., 2018). Alternative feedstock sources and

Abbreviations: EROI, energy return on investment; GHG, greenhouse gas; LCA, life-cycle assessment; LUC, land use change; TAP, terrestrial acidification potential.

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processes involving lignocellulosic biomass have been promoted to alleviate the food *vs.* fuel competition and improve the environmental performance of biofuels (Tilman et al., 2009; El Akkari et al., 2018).

Aside from crops or forest residues, perennial energy crops stand out as sources of lignocellulose due to their capacity to sustain high biomass yields and their large GHG abatement potential. Species such as miscanthus (*Miscanthus giganteus*) and switchgrass (*Panicum virgatum*) are promoted for bioethanol production because they have higher light, water, and nitrogen use efficiency and provide larger environmental benefits than cereals and sugar crops (Tilman et al., 2009). Both species have been documented to be particularly well suited to the temperate regions of the US and Europe (Lewandowski et al., 2016), while recent reports suggested expanding their production through genetic plasticity (Clifton-Brown et al., 2017). Miscanthus can translocate mineral nutrients and carbohydrates from leaves and stems to rhizomes between two growing seasons, thus reducing or eliminating the needs for mineral fertilizers (Dohleman and Long, 2009). Switchgrass is an inherently N-thrifty plant, especially when managed for biomass production (Parrish and Fike, 2005). Both miscanthus and switchgrass require fewer chemical inputs than annual crops (Sokhansanj et al., 2009), produce large quantity of biomass and provide other important ecosystem services (Lewandowski and Heinz, 2003).

To address the sustainability of bioethanol production systems, it is important to account for land use competition and transitions, and the spatial distribution of crops as well as logistics constraints in relation to local conditions (Petersen et al., 2015; Hellmann and Verburg, 2011; Perrin et al., 2017). Life cycle assessment (LCA) has been extensively used to gain insights into the potential environmental impacts of biofuel systems. Earlier LCA studies concluded that cellulosic ethanol (also referred to as 2nd generation bioethanol) had a positive energy balance and could help secure a domestic supply of energy (Cherubini et al., 2010; Schmer et al., 2008) while being more energy efficient than its 1st generation counterparts and leading to larger GHG savings (Whitaker et al., 2010; Farrell et al., 2006; El Akkari et al., 2018). However, they were criticized for their narrow system boundaries and inabilities to capture land use change (LUC) effects, which are key drivers of the GHG balance of cellulosic biofuels (Jeswin et al., 2020). LUC effects may be both positive at the local scale (through soil C sequestration arising from the transition to perennial crops) and negative at the global scale due to indirect LUC occurring elsewhere (Berndes et al., 2013; Gabrielle et al., 2014). Thus, it is important to factor in both types of LUC to assess their overall balance. Models simulating farm economics of farms at the regional scale provide a state-of-the-art means of capturing the effect that an increase in biofuel demand (a demand shock) would cause farmland reallocation in the biorefinery's supply area. They have been used to anticipate the type of land transitions incurred by such a shock (Ben Fradj and Jayet, 2018) or to estimate GHG emissions (Hudiburg et al., 2016), but not in combination with complete LCAs so far.

Other limitations of previous assessments is that they ignored to a large extent the specific spatial context of agricultural production systems (Hellweg and Mila i Canals, 2014). Yet location matters, especially for biofuel feedstocks. Indeed, the type of cellulosic energy crops cultivated and their biomass yields vary strongly according to the local and regional conditions (e.g., soil properties, climate conditions or crop management), and so do the environmental impacts of bioethanol (Dufossé et al., 2016). Moreover, local factors such as soil pH or buffering capacity not only affect yields, but also the impacts of crop production on the acidification of soils or water bodies (Sinistore et al., 2015). Beyond crop production, feedstock processing and conversion to bioethanol can also entail significant regional variations in the overall performance of cellulosic biofuels (Hudiburg et al., 2016). The location of conversion plants plays a key role in the environmental impacts of biofuels through fuel consumption during the transport of feedstock to the biorefinery. Therefore, spatially-explicit LCAs are needed to evaluate the actual GHG abatement potential of biofuels, and possible trade-offs with other impact categories at the regional scale (Hellweg et Mila i Canals, 2014; Dufossé et al., 2013). Combining LCA with agroecosystem models (Gabrielle et al., 2014; Hudiburg et al., 2016) is an interesting option to improve on this point, to map out crop yields, soil C variations and the emissions of reactive nitrogen in the inventory step.

Here, we set out to better address reactive nitrogen emissions and LUC effects in the environmental assessment of bioethanol at the regional level in France, by combining biophysical, economic models and LCA. Compared to the pioneering work by (Hudiburg et al., 2016) in this direction, which focused on the effect of biofuel policies on land-use and the GHG emissions of cellulosic biofuels in the US, we used a broader set of environmental indicators (including global warming, energy efficiency, eutrophication and acidification potentials), and investigated two agronomic options to produce the biomass feedstock: two candidate crops (miscanthus and switchgrass), and various fertilizer N input rates. Here we modelled the land use changes and its GHG emissions related to increase bioethanol demand in France. A second objective of this modelling exercise was to capture variations in environmental impacts within and across regions, and to identify in which regions cellulosic ethanol achieved the highest performance.

2. Material and methods

2.1. Overview of assessment methodology

In this paper, we combined the agro-ecosystem model CERES-EGC, the economic farm model AROPAj, and the LCA approach to investigate both the supply chain and the spatial distribution of environmental impacts of miscanthus and switchgrass-based bioethanol over France. In this combination, CERES-EGC was used to simulate the growth and field emissions of miscanthus and switchgrass (El Akkari et al., 2020). The AROPAj model was used to assess direct effects of feedstock production on land and to optimize the establishment patterns and management of both crops at regional level (Ben Fradj et al., 2016; Ben Fradj and Jayet, 2018). Outputs of the AROPAj model were combined with the data on crop yields and field emissions from CERES-EGC, along with data on crop cultivation and bioethanol conversion processes to develop the LCA model for bioethanol production in France. A number of crop management scenarios were implemented using the SimaPro v.9.0 software package (PRé Sustainability, Amersfoort, NL), involving various rates of fertilizer N application (see below section).

2.2. Simulation of miscanthus and switchgrass growth

The CERES-EGC model uses daily weather data, together with a set of parameters describing crop, soil and management factors to simulate miscanthus and switchgrass growth over the growing season. The model computes biomass yields, as a function of water, solar radiation, and soil temperature and limits actual growth based on soil nutrient availability. Model outputs include harvested yields, soil carbon uptake and loss, direct N_2O emissions, emissions of nitric oxide (NO) and ammonia (NH3) and nitrate leaching. To use the model over the France (metropolitan) domain, it was necessary to obtain local values of the above parameters. The model required the following inputs: daily precipitation and temperature, soil texture and depth, and crop management practices. Four annual N input rates were tested: no input (0 kg N ha^{-1}), and low (30 kg N ha^{-1}), medium (60 kg N ha^{-1}), and high rates (90 kg N ha^{-1}).

2.3. Simulations of regional farmland reallocation and land use changes

AROPAj was applied at farm group level to evaluate land use changes resulting from the integration of new crop activities, *i.e.*, miscanthus and switchgrass in this case. To provide relevant and accurate impact analyses, non-linear production curves relating input level to yield potential of major arable and lignocellulosic biomass crops were estimated through a linkage with two biophysical models. While the generic crop model STICS was used to estimate crop yield response to N and water of soft and durum wheat, barley, sugar beet, potatoes, rapeseed, sunflower and soya (Humblot et al., 2017), the N yield response of miscanthus and switchgrass were simulated with CERES-EGC.

The modeling of lignocellulosic crops involved a four-step procedure. CERES-EGC was first used to simulate the N-yield responses of miscanthus and switchgrass over a 25-year horizon (from 2010 to 2035) across 4 N input rates varying from 0 to 90 kg N ha^{-1} in 30 kg N ha^{-1} increments. The response functions were then calibrated and input to AROPAj based on a non-linear estimation of the technical production that considers both the dynamics of plant growth and the N-input level applied at each year during a rotation cycle. Thirdly, an inter-temporal optimization program was used to determine the optimal rotation period and N-input level that maximize farmers' profitability. Lastly, optimal annual costs, price, and response function parameters were called by the AROPAj model to return the optimal output for each activity and optimal land allocation at farm group level. The main output of interest for the LCA was the land use changes in terms of crop acreage and type of land (grassland or cropland) that miscanthus or switchgrass would substitute. A maximum conversion rate of 5 % of the total cropland area was assumed in this analysis (Emmerling and Pude, 2017).

2.4. Life cycle assessment

2.4.1. Functional unit and system boundary

The assessment followed the ISO standards for LCA (ISO, 2006). We used one MJ of bioethanol (produced at the biorefinery gate) as the functional unit. The bioethanol system involved 3 main stages (Fig. 1): feedstock production, transport to the biofuel production unit, and conversion into bioethanol. The geographical boundaries are France for the production and transport of miscanthus/switchgrass and Europe for conversion of miscanthus to bioethanol. The time boundary is set to 5–10 years. After this period of time, the data used in this assessment may no longer be applicable and undermine its validity.

2.4.2. Feedstock production

This step includes the activities and inputs/outputs and impacts associated with the production and harvest of miscanthus/switchgrass biomass. The rotation cycle of the two crops was set to 25 years. The first cropping year is characterized by soil preparation, planting and herbicide application, in the absence of fertilizer inputs. Miscanthus was established through rhizomes at 15 000 rhizomes ha^{-1} while switchgrass was established using seeds at 1500 kg ha^{-1}. No fertilizer was applied at the establishment year in all regions of France for both crops. From the second year until the last one (year 25), the management consists of a single application of fertilizers (with varying rates) and a late (winter) cut. Applied N ranged from 0 to 90 kg N ha^{-1}. Harvest was completed with conventional hay equipment. During the harvesting, both crops are, field dried, baled and loaded on diesel truck-trailer and transported to the farm group where it is temporarily stored. The last year involves the destruction of crop. Crop management data are detailed in Table 1, according to the crop growing cycles.

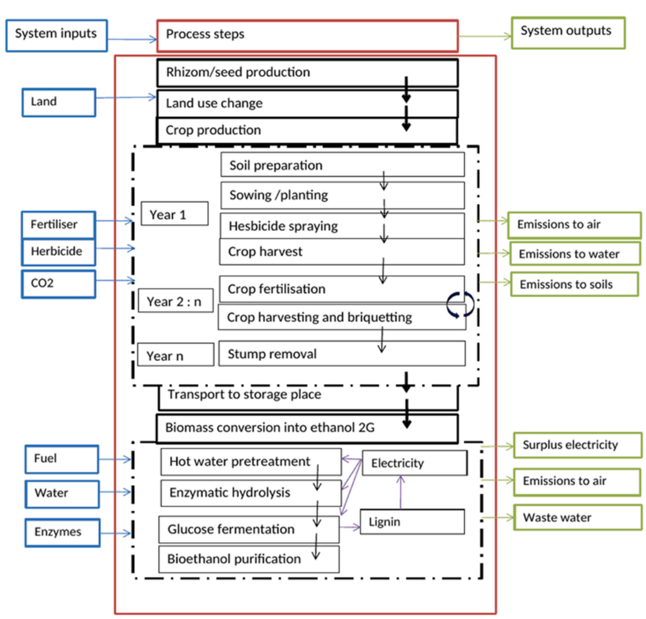

Fig. 1. System boundaries for ethanol production from miscanthus and switchgrass.

2.4.3. Transport

The transport of miscanthus rhizomes and switchgrass seed to farm was done using a 16 ton-truck over a distance of 10 km. The transport of miscanthus and switchgrass biomass to bioethanol plants was done by trucks (with a capacity of 20 t). The location of these units was defined depending on the feedstock supply potential of the different regions. If a region produced an enough biomass to meet the demand of one biorefinery, a unit was located in this region, otherwise neighboring regions were explored to meet the same demand and determine the best location of a biorefinery.

2.4.4. Biomass conversion to ethanol

For the conversion to bioethanol, we considered similar processes and data for both feedstocks (miscanthus and switchgrass): biochemical conversion with a hot water biomass pre-treatment. The chosen conversion plant has a production capacity of 40 kt ethanol per annum, which performed best according to a previous benchmarking study (Lask et al., 2019). The lignin from the pretreatment process was subsequently combusted to produce heat and power. The produced electricity was sufficient to cover the bioethanol plant's electricity demand whereas a small amount of heat was sourced from the district heating network to meet the total heat demand of the bioethanol plant. Enzymes use in biochemical process are based on information from (Lask et al. 2019).

2.4.5. Allocation

No, allocation was needed for the feedstock production stage because the cultivation of miscanthus or switchgrass does not generate any co-product upon harvest, and the whole biomass from these crops is used for bioethanol production. Lignin is generated as a co-product during the pre-treatment and fermentation of both crops to bioethanol. This lignin was subsequently burnt to produce heat and power, which were all used to cover the energy demand of the biorefinery. Thus, no allocation was also need in the biomass conversion stage as the produced heat and power were consumed within the bioethanol plant.

Table 1
Data used in the life cycle inventory.

Crop Management	Soil preparation, planting and harvesting	Literature (Besnard et al., 2013)
	Fertilizer inputs	0, 30, 60 and 90 kg N ha-1 yr-1
	Agricultural Machinery	Agribalyse v3.0.1
	Yield	CERES- EGC
	Direct Nitrogen Emissions	CERES- EGC
	Soil carbon stock variations	CERES-EGC & AROPAj
Logistics	Transportation Distance	Own Calculation
	Truck and trailers	Agribalyse v3.0.1
Conversion	Process data	Literature (Lask et al., 2019)
	Equipment data	Ecoinvent v3.4
	Emissions data	Ecoinvent v3.4

2.4.6. Data collection and treatment

Data used for the LCA originated from different sources, including literature data, the CERES-EGC and AROPAj outputs data, as well as data from the Ecoinvent v3.4 database (Hischier et al., 2010), complemented with the Agribalyse (v3.0.1), a database for the agricultural sector in France (Koch and Salou, 2013). The regional data simulated by the ecosystem and farm models are detailed in Appendix A, the logistics data appear in Appendix B, while the inventory data related to feedstock production and conversion into ethanol appear in Appendix C. Table 1 summarizes the main data sources used for the various sub-systems.

The outputs of the bioeconomic modelling with the AROPAj model were used to calculate the regional variations of cropland area following the introduction of miscanthus or switchgrass, with the constraint that only 5 % of cropland could be converted at most. The initial cropland areas were taken from the farm accountancy data network (FADN) for the year 2010 (Cantelaube et al., 2012). The variations in cropland areas involve the following crop types or land-use classes: cereals, root crops, oilseeds, legumes, industrial crops (*i.e.* non-food crops such as tobacco and flax), fodders, grassland and fallow land. These types were subsequently grouped into land-use classes: cropland, industrial crops, grassland and fallow land. At the regional scale, the effect of direct LUC on soil organic C stocks (SOC) was calculated as follows. First, the initial regional soil carbon stock (C_{T0}, in t C ha-1) was averaged over the main land-use classes using the following equation:

$$C_{T0} = \alpha_1 C_{CL} + \alpha_2 C_{GL} + \alpha_3 C_P + \alpha_4 C_{OL} \tag{1}$$

With $\sum \alpha_i = 100$ % at the start of simulations, and where α represent the share of given land type in total land use. C is the carbon stock corresponding to land-use class; and the indices CL = cropland, GL = grassland, P = pasture; OL = other land.

After application of the biofuel demand shock, the new regional SOC stock was calculated as:

$$C_{T1} = \beta_1 C_{CL} + \beta_2 C_{GL} + \beta_3 C_P + \beta_4 C_{OL} \tag{2}$$

With $\sum \beta_i = 100$ % after the biofuel demand shock and where β represent the share of given land type in total land use. The SOC variation between T0 and T1 was then calculated as:

$$\Delta C = C_{T0-1} = (\alpha_1 - \beta_1) C_{CL} + (\alpha_2 - \beta_2) C_{GL} + (\alpha_3 - \beta_3) C_P + (\alpha_4 - \beta_4) C_{OL} \tag{3}$$

Thus, ΔC represents the variation of SOC related to direct and indirect land use changes due to the biofuel demand shock over the region. The carbon stocks of the different land classes were retrieved from the literature (Table 2), to account for variations attributable to the transition from grassland, fallow or cropland to miscanthus or switchgrass.

Table 2
Soil carbon sequestration rates and soil C stocks used for the estimation of C emissions from land transformation.

Land-use transition or initial land-use	Values	Units	Sources
SOC variations			
Transition from cropland to miscanthus	Regional averages	t C ha^{-1} yr^{-1}	CERES-EGC simulations
Transition from grassland to miscanthus	0.84	t C ha^{-1} yr^{-1}	Ferchaud et al. (2016)
Transition from grassland to switchgrass	0.64	t C ha^{-1} yr^{-1}	Ferchaud et al. (2016)
Initial soil carbon stock			
Cropland	52	t C ha^{-1}	Pellerin et al. (2017)
Industrial crops	79	t C ha^{-1}	Pellerin et al. (2017)
Grassland	85	t C ha^{-1}	Pellerin et al. (2017)
Fallow land	80	t C ha^{-1}	Pellerin et al. (2017)

The values were simulated by CERES-EGC for cropland transitions and taken from a literature review for the grassland transitions (Table 2).

2.4.7. Impacts categories and LCA simulation

The impact categories studied include global warming potential, terrestrial acidification potential, eutrophication potential, land transformation, and non-renewable energy use, based on the IMPACT 2002+ characterization method. In addition, we determined the energy efficiency (i.e., energy return on energy invested (EROI)) of bioethanol by dividing the energy content of bioethanol by the cumulative non-renewable energy used to produce it. The modeling of bioethanol system was carried-out using SimaPro v9.0 (Pré-Sustainability, 2015).

3. Results and discussion

3.1. Direct land-use changes and SOC variations

Table 3 summarizes the changes in land-use entailed by the deployment of miscanthus and switchgrass in France, for the main land-uses simulated by AROPAj (see Appendices D and E for more details). The area in industrial crops changed very little compared to areas under other crop types. Cropland was the most affected and initially predominant type of land-use in all regions of France, with an overall share of 82 %. Grasslands made up 12 % of the utilizable agricultural area in 2010, and its area also decreased after the integration of miscanthus and switchgrass, to an extent that differed across regions. In Brittany, for example, 99 kha of non-energy cropland were lost compared to the baseline, and energy crops were mainly established on cropland. This trend applied in general except in the Limousin region where 25.7 kha of energy crops were established on grassland. In the Centre region there was a balance between cropland and grassland in the transition to energy crops, involving areas of 25.4 kha and 21.3 kha, respectively. Conversely, fallow land increased by 34 kha overall, and energy crops took up 736 kha in total (making up 4.9 % of the total UAA of France, around the upper bound prescribed in the simulations).

Soil C sequestration represents a very important item in the quantification of GHG emissions from biomass feedstock, with an overall effect on soil C stocks which can be positive or negative (Richard et al., 2017). This depends on crop type but also management practices (eg fertilizer N rate; Davis et al., 2012), local pedoclimatic conditions and also on the previous crop or land-use transition (Don et al., 2012; Richards et al., 2017). Previous land-use and crops also have a large influence on direct LUC effects.

Soil C variations estimated from the CERES-EGC and AROPAj simulations are detailed in Appendix A. They were mostly positive except for the unfertilized crops, with large inter-regional variations. Soil C sequestration rates were significant, especially for miscanthus with a 0.10–0.39 t C ha^{-1} yr^{-1} range. This was still lower than the median of 0.66 Mg C ha^{-1} yr^{-1} rate suggested by Don et al. (2011) for miscanthus in their literature review. Note that in our study we factor in indirect effects at regional scale on soil C stocks, so soil C variations estimated at the regional level are not directly comparable to field-scale data.

3.2. GHG emissions of crop production

Here, we focus on GHG emissions from the production of biomass feedstock (whether from miscanthus or switchgrass) and their regional variations over France.

When aggregated at the national level, GHG emissions per kg of dry matter (DM) differed substantially across the two crops (Fig. 2). They varied within a - 6.7 to 238.6 g CO_2-eq. kg^{-1} DM for miscanthus, against a -179.5 to 290.4 g CO_2-eq. kg^{-1} DM range for switchgrass. Switchgrass emitted on average 32 g CO_2-eq. kg^{-1} DM more than miscanthus, and this spread was even larger within a given region, with differences reaching up to 197 g CO2-eq. kg-1 DM (data not shown). The differences in GHG budgets between the two crops are linked to their particular

Table 3
Variations in agricultural area (kha) among the main land-uses simulated by AROPAj following the deployment of energy crops (miscanthus and switchgrass) relative to the 2010 baseline in France. The region acronyms are defined in Appendix F.

Region	Cropland	Industrial crops	Grassland	Fallow	Energy crops	Total area (kha)
IDF	-5.67	-0.06	-0.08	-1.06	6.86	545.38
Champ A	-65.57	-0.24	-0.014	-4.20	69.92	1433.5
Picardie	-20.13	-0.33	1.10	-1.51	20.84	1251.5
Hnorm	-5.55	-0.15	-3.04	0	8.74	744.23
NordPC	-74.59	0	2.49	-2.90	74.92	2228.36
Centre	-25.36	-0.46	-21.34	-0.78	47.93	1134.82
Bnorm	-32.48	0	-12.51	-0.32	45.3	1611.7
Bourgogne	-17.40	-0.42	5.39	-0.17	12.57	782.59
Lorraine	-18.44	0	2.26	0	16.18	1105.3
Alsace	-8.00	-0.006	-0.007	-0.66	8.66	259.52
Loire	-11.96	0	0.29	-2.44	14.11	648.18
Bretagne	-99.93	-0.24	-6.15	23.39	82.91	2026.04
FrancheC	-31.37	0	-2.37	1.47	32.25	1560.58
Poitou	-35.30	-0.001	-9.16	-5.11	49.56	1489.19
Aquitaine	-74.05	-0.09	5.54	25.89	42.68	931.84
MidiPy	-66.43	-0.09	-9.35	-6.37	82.23	1825.65
Limousin	3.65	-0.05	-25.70	0	22.08	702.65
Rhone A	-54.05	-0.09	0.29	8.21	45.62	1164.54
Auvergne	-23.88	-0.009	-19.60	4.18	39.29	1319.92
Lang	-7.18	0	-2.75	-3.17	13.1	268.55

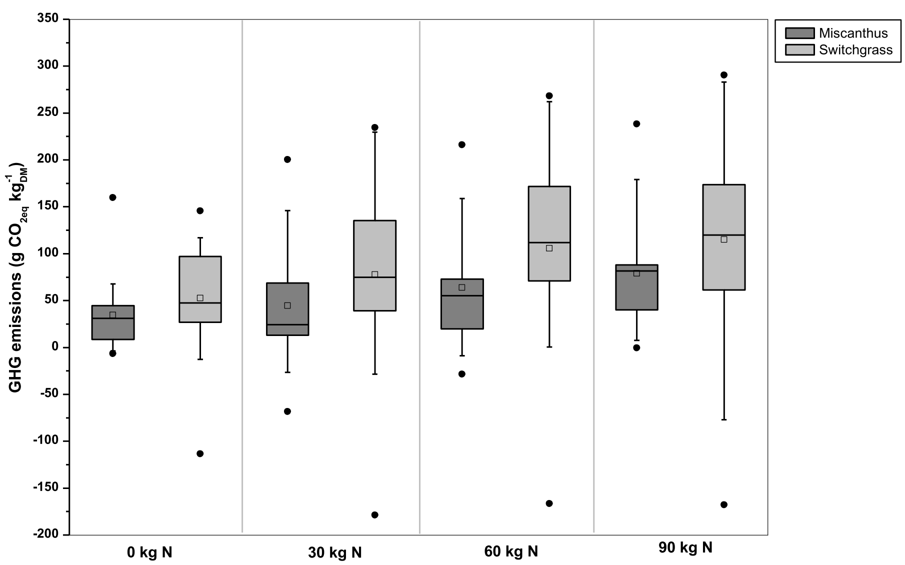

Fig. 2. Boxplots of life cycle GHG emissions of the farming stage of miscanthus and switchgrass biomass production over France, as a function of fertilizer N rates. Lines indicate the 25th, 50th and 75th percentiles, respectively, while the circles indicate outliers.

ecophysiological traits. Miscanthus tends to develop larger rhizomes and therefore to transfer more carbon into soils than switchgrass between growing seasons. Thus, it is more productive on average (Laurent et al., 2015), and stored more C in soils than switchgrass (Appendix A). The latter also emitted 36 % more N_2O overall per ha due to its lower productivity and N use efficiency (see Appendix A). Although the establishment of miscanthus involves rhizome planting, which is more resource-intensive than the sowing of seeds for switchgrass, this disadvantage was more than compensated for by the other factors driving the crops' GHG balances.

The spread of the boxplots on Fig. 2 points to a large inter-regional variability. If we take for instance the 60 kg N ha^{-1} fertilizer N input rate, the maximum GHG budget for miscanthus are recorded in the PACA region with 216 g CO_2-eq. kg^{-1} DM and the minimum in the Ile de France (IDF) with -29 g CO_2-eq. kg^{-1} DM. With regard to switchgrass, the maximum GHG budgets are recorded in Champagne-Ardennes with 262 g CO_2-eq. kg^{-1} DM and the minimum is recorded in Picardy at -166 g CO_2-eq. kg^{-1} DM. Emissions were very contrasted between regions, with some of them incurring negative emissions at crop production level. This variation is strongly linked to the pedoclimatic conditions which impacted not only the yield but also favored soil carbon storage rate and reduced reactive nitrogen emissions in some regions (Appendix A). Such variability was reported in spatially-explicit assessment of transitions to energy crops or reviews of site observations (Richards et al., 2017) and confirms the importance of using spatially-explicit modelling to consider local pedoclimatic conditions and thus reduce the uncertainties of life cycle inventory data (Dufossé et al., 2013).

Regarding the response of emissions to the N input dose we note that for miscanthus the highest emissions are recorded with the unfertilized controls. This is due to a very low soil C storage recorded for this level of fertilization, since this sequestration rate increased with increasing N input rates (Appendix A). This is consistent with a high-resolution study of energy crops in the UK reporting that soil C sequestration rates correlates with higher biomass yields for miscanthus (Richards et al., 2017).

3.3. GHG emissions of bioethanol production

Fig. 3 depicts the GHG balances of the entire bioethanol supply-

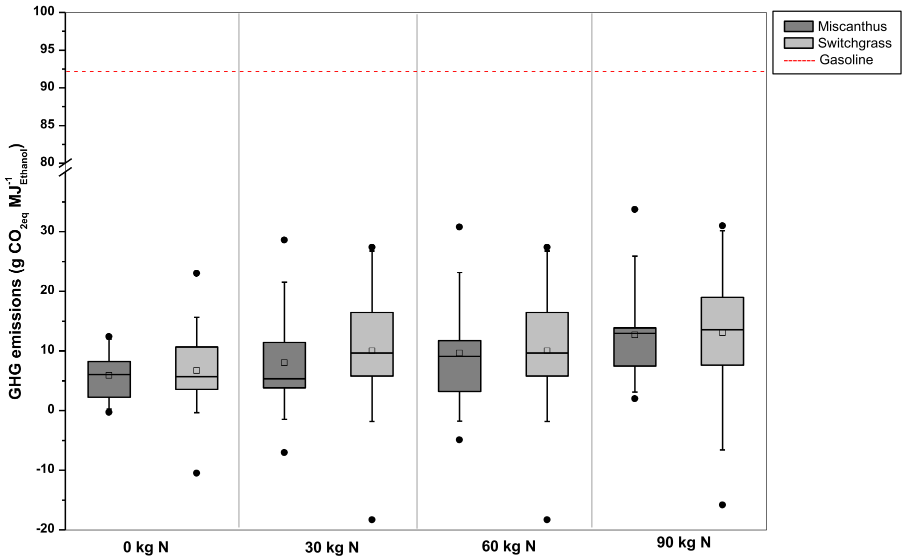

Fig. 3. Boxplots of GHG emissions of cellulosic ethanol production from miscanthus and switchgrass as a function of fertilizer N input rates.

chains including biomass production, transportation and conversion into ethanol, as a function of fertilizer input rates. GHG budgets followed a pattern similar to those of biomass production (Fig. 2), given that biomass pre-treatment and conversion processes were identical for both feedstocks. The Figure shows that from a GHG balance perspective, the optimum nitrogen input rate for crops was the unfertilized control for switchgrass, and the next higher rate (30 kg N ha-1 yr-1) for miscanthus. Note that these optimal rates do not maximize biomass production per hectare. These agronomic optima were higher by 30 kg N ha-1 yr-1 for both crops (see Appendix A). The fact that they differ from the environmental optima is not surprising since N inputs increase N2O emissions and energy use per hectare, at a rate which may not be compensated by the extra biomass produced. This was also noted for wheat energy consumption in the UK (Brentrup et al., 2004).

Overall, switchgrass-based bioethanol emitted 1.3 times more GHG than its miscanthus counterpart, with an average emission of 11 gCO_2eq MJ^{-1} compared to 9 g CO_2eq MJ^{-1} for miscanthus. Such significant difference in the global warming impacts of these two bioethanol pathways was mainly driven by the differences in soil carbon change and nitrous emissions, which were key contributing processes to the life cycle global warming impacts of both crops. The emission values in this study agree well with those reported by Wang et al. (2012) for switchgrass (12 g CO_2eq. MJ^{-1}), but much higher than their estimate for miscanthus (-7 g CO_2eq. MJ^{-1}) in the US. Our emission estimates are, however, lower than the range reported by Lask et al. (2019) for miscanthus-based ethanol in Europe (29.0–61.0 g CO_2eq. MJ^{-1}). The handling of co-products (in particular the surplus electricity) explains part of the differences between these two studies, and also our calculations. In fact, a large fraction of electricity cogenerated from the lignin was exported to the grid in these two studies whereas in our study most of the coproduced electricity was used within the biorefinery and only a very small fraction was exported to the grid.

The potential of bioethanol to abate GHG emissions compared to gasoline was assessed using an emission rate of 92.3 gCO_2eq MJ^{-1} for the latter (ADEME, 2010). Abatement rates ranged from 74 % to 91 % (for switchgrass) and from 86 % to 94 % (for miscanthus) across regions and N input rates, which were somewhat narrower and slightly lower than reported by Wang et al. (2012) in the US (with a 77–97 % range for switchgrass and a 101–115 % for miscanthus). Lask et al. (2019) reported savings of 65 to 103 % for the miscanthus pathway with the optimal pre-treatment process, which we had selected here. Monti et al. (2012) reported GHG savings of 63 % to 118 % for cellulosic ethanol relative to gasoline, based on a literature review. Our GHG emission's abatement rates fall within these reported ranges. Note that the emission abatements above are based on a 100 % replacement of gasoline by bioethanol, which is rarely practiced in many countries. In France, a mixture of gasoline and up to 85 % bioethanol (E-85) is allowed. Consequently, assuming 85 vol % bioethanol in the gasoline would lead to a 58–72 % saving of GHG emissions for switchgrass and 68–74 % saving of GHG emissions per megajoule of fuel. These latest emission abatements still complied with the minimum 50 % abatement target for all bioethanol as specified by the Renewable Energy Directive (directive 2009/28/EC) of the European Union (European Parliament, 2009).

Our estimates of GHG emissions of miscanthus and switchgrass-based bioethanol agreed with values reported in the literature. Reported GHG emissions for miscanthus-based bioethanol vary from -1 to 55 gCO_2 MJ^{-1} (average: 27 gCO_2 MJ^{-1}), whereas that of switchgrass-based bioethanol range from 1 to 52 gCO_2 MJ^{-1} (average: 30 gCO_2 MJ^{-1}) (Jeswani et al., 2020). Differences between studies in the literature and ours reflect the different growing conditions of these feedstocks, the production pathways, technologies used, system boundaries, data and assumptions. As in our study, most of the literature studies considered the land use change and SOC sequestration associated with feedstock cultivation (Qin et al., 2016). Despite the difference in estimates, our study corroborated previous findings that GHG emissions of lignocellulosic biofuels are lower than those of fossil fuels (Falano et al., 2014).

3.4. Contribution analysis of the different stages of the biofuel production chain to GHG emissions

Fig. 4 details the contribution of each item in the biofuel production chains for miscanthus with the 60 kg N ha^{-1} N input rate (the agronomic optimal rate). Biomass production proved consistently the most impactful step, accounting for 20–30 % of the positive life cycle emissions. Other steps contributed similarly regardless of fertilizer input rates, region of production or crop type (the results for switchgrass are not shown on Fig. 4 but were very similar). Similar to Lask et al. (2019), conversion to ethanol was the second hotspot, in particular due to the consumption of process water and enzymes. The other steps in the value-chain were more dependent on crop type and fertilizer input rate (this is especially the case for the biomass production step) or the region (which affected logistics and transportation distances). Transport-related emissions were highly variable between regions and crops, with average collection distances ranging from 31 to 59 kms, one way (Appendix B). Higher crop yields in a given region reduced this

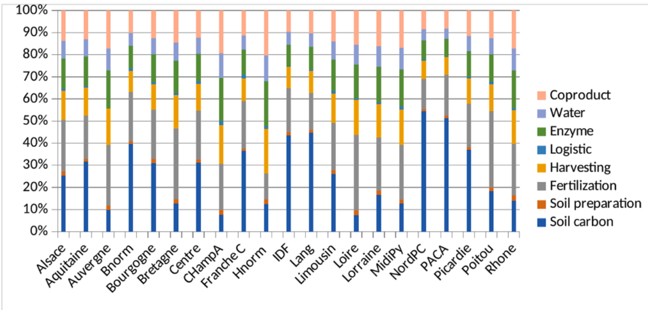

Fig. 4. Contribution analysis for the GHG emissions of bioethanol production from miscanthus in the various regions of France, for the 60 kg N ha^{-1} fertilizer input rate. Water: use of process water for ethanol production. Co-product: credit for the substitution electricity to the grid. See map in Appendix C for the location and names of regions.

transportation distance, while in some cases the regional biomass output was too low to meet the demand of a single biorefinery and the unit (biorefinery) was supplied by several regions, increasing the mean transportation distance. This explains why switchgrass-based ethanol was out-performed by its miscanthus-based counterpart in general, with 30 % larger transportation distances.

The two steps with generally beneficial effects on GHG emissions are soil carbon sequestration and the cogeneration of electricity and heat from the lignin co-product in the conversion stage. This energy production reduced the overall emissions of bioethanol by 2.4 g CO_2eq MJ^{-1} biofuel on average. Note that the credit from the electricity co-product is highly dependent on the CO_2 content of the electricity substituted. Here we used the average GHG-intensity of the French electricity mix (metropolitan), which has a low CO_2-intensity (60 g CO_2-eq. kWh^{-1}) due to its large share of nuclear power.

3.5. Energy efficiency and non-GHG environmental impacts

The non-renewable energy use of switchgrass was higher than that of miscanthus (Fig. 5a) due to its lower productivity. Fig. 5b presents the energy efficiencies (EROI) of the bioethanol chains under different fertilization rates, defined as the ratio of energy units contained in the bioethanol to the energy units consumed to produce the fuel. This ratio is understood as the efficiency of the bioethanol system at converting non-renewable energy into renewable energy carrier directly utilizable for transport. An alternative to fossil fuel must have lesser negative impacts on environment, meaning that it EROI must be greater than unity (Wang et al. 2012). Clearly, miscanthus is more energy efficient than switchgrass as a feedstock for bioethanol production, while bioethanol from both crops still provides net energy gain: average EROI was 4 and 4.5 for switchgrass and miscanthus-based bioethanol, respectively (Fig. 5b). An EROI smaller than unity would mean that more non-renewable energy is used than create to operate the bioethanol system, which could jeopardize energy security and potentially nullify the CO_2 emission savings provided by bioethanol.

For both feedstocks, the EROI decreased as N input rates increased (Fig. 5b), meaning that the gain in biomass yields could not compensate for the energy intensity of the added (synthetic) fertilizer N. It is possible to improve energy efficiency and reduce GHG emissions of miscanthus and switchgrass based bioethanol through the recycling of lignin to produce process heat and electricity (Lask et al., 2019). This is indeed the case in this study, where lignin is converted into heat and electricity directly used in the bioethanol conversion unit. This internal recycling of lignin reduces the fossil energy demands, and thus improves the EROI and GHG balance of the bioethanol.

EROI values obtained in this study for miscanthus- and switchgrass-based bioethanol are very encouraging and corroborate previous findings on EROI of lignocellulosic biofuel. Indeed, previous biofuel studies showed that the EROIs of lignocellulosic bioethanol vary from 4 to 11 (Harmerschlag, 2006; Farrell et al., 2006; Wu et al. 2006). However, Pimentel and Patzek (2005) found EROI values < 1. The main difference between the latter studies and ours is their assumption that bioethanol refineries would use fossil fuels rather than the lignin residues from pretreatment, and enzymatic hydrolysis to generate their process energy requirements.

Besides the non-renewable energy consumption and GHG emissions,

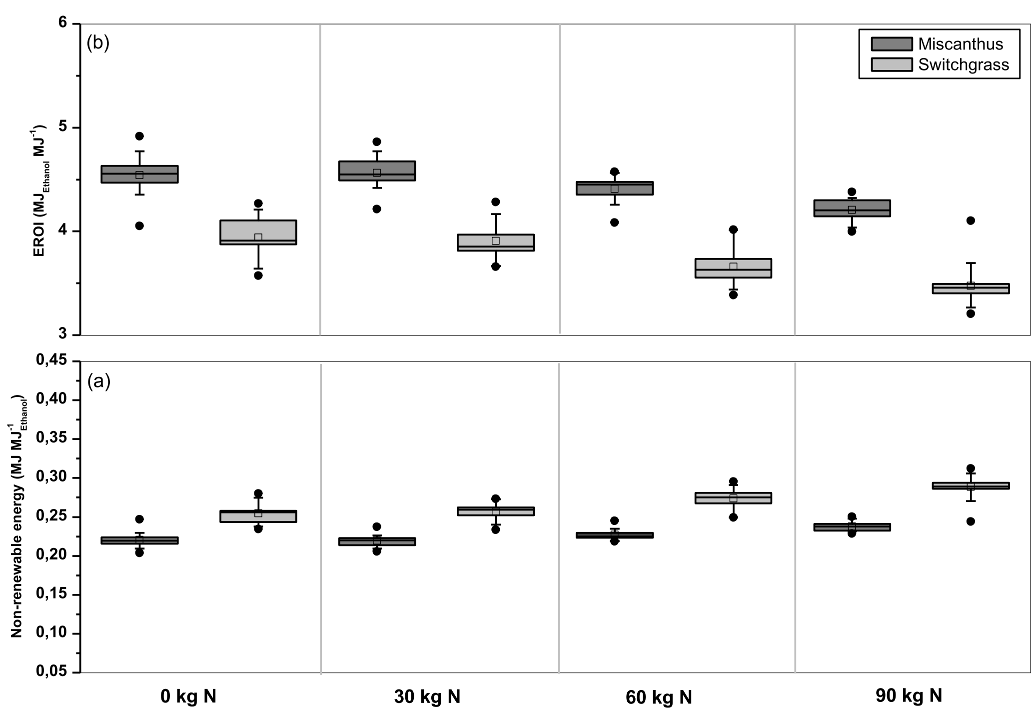

Fig. 5. Boxplots of energy efficiency metrics (expressed as the Energy Return on Investment, EROI) of miscanthus- and switchgrass-based ethanol in France, as a function of fertilizer N input rates.

two other environmental impacts namely terrestrial acidification (AP) and aquatic eutrophication (EP) were investigated. As is usually the case in the life cycle of cellulosic bioethanol, these two impacts were mainly related to the agricultural phase. Consistent to other impacts categories, the AP were higher for switchgrass (with an average of 1.14 g SO_2-eq. MJ^{-1}) than for miscanthus (average 0.98 g SO_2-eq. MJ^{-1}; Fig. 6a), highlighting the differences in yields and N use efficiency between the two crops. Fertilizer N-induced emissions especially ammonia had the highest impact on AP for both crops, followed by the production of nitrogen fertilizer and transport of biomass. Above the optimal N input rate, surplus N stands higher chances of being lost, in particular in gaseous forms. Since the optimum N input rate for switchgrass was lower than for miscanthus (at 30 kg N ha^{-1}), the response of AP to N inputs was stronger. This also occurs because of the lower N use efficiency noted for this crop. The results were similar for aquatic eutrophication (Fig. 6b): miscanthus-based bioethanol (with an average of 0.17 g PO_4^{3-}-eq. MJ^{-1}) was less impactful than switchgrass-based bioethanol (average = 0.19 g PO_4^{3-}-eq. MJ^{-1}) and emissions depended on the fertilization rate (Fig. 6b). The pattern of the EP impact reflects the spatial distribution and magnitude of on-farm nutrient releases, since leaching and run-off were leading contributors to EP throughout the different regions of France, accounting for 85 % of the total EP impacts, while the production of phosphorus fertilizer contributed to about 9 % (data not shown).

One of the limitations of this study is that it neither assesses the water use and water quality, nor the food security issues associated with miscanthus- or switchgrass-based bioethanol. However, bioethanol production relies on large volumes of water across its different supply chain stages (Gerbens-Leenes et al., 2014). Water use of bioethanol consist of green water (i.e., rain & soil), blue water (surface and ground water) and grey water (water required to dilute pollutant flows into the environment) (Mekonnen and Hoekstra, 2011). Studies show that water use of bioethanol occur predominantly during feedstock production and depend on feedstock types, crop yields, difference in climate, and agricultural practices (Wu et al., 2014). The blue water use of miscanthus and switchgrass bioethanol in the literature is estimated at 8 m^3/GJ and 2 m^3/GJ, respectively (Wu et al., 2014). These estimates are lower than that of 1st generation bioethanol from food crops (0–34 m^3 GJ^{-1} (Mekonnen and Hoekstra, 2011), but higher than the blue water use of conventional fossil fuels (0.036 to 0.140 m^3 GJ^{-1}) (Spang et al. 2014).

With regard to food security, the increasing use of food and feed crops for bioethanol production competes directly with their use for food, causing prices of food to rise as supplies tighten (Tangermann, 2008). Although miscanthus and switchgrass are not a not edible crops for humans, they still require land for their cultivation and the land requirement can be substantial if its biomass yields are low, still exacerbating potential land use conflicts (Thompson, 2012). This undermines the sustainability of 2nd generation biofuels, and requires a continuous scrutiny as the latter develop. One strategy of avoiding food vs fuel debate is the development of miscanthus on marginal or degraded lands which are unsuitable for food production (Njakou-Djomo et al., 2023; Krzyżaniak et al., 2020).

4. Conclusions

Second generation bioethanol represents a good choice for reducing GHG emissions on the scale of France, with an abatement potential in the 86–94 % range for miscanthus and 74–91 % for switchgrass compared to gasoline. Overall, miscanthus proved more productive and less impactful than switchgrass as lignocellulosic feedstock candidate. Its superior performance in terms of GHG balances was also and mainly related to its larger soil C sequestration potential. Fertilizer N input rates had a large effect on the environmental performance of both feedstocks, emphasizing the importance of seeking and applying optimal N doses, according to the bioeconomic simulations. Given the large inter-regional variability revealed by this modeling exercise, the use of spatially-explicit and process-based models appears as a promising avenue to reduce uncertainties in the life cycle assessment and in the planning of bioethanol units. Most of the environmental impacts depend on the regional pedoclimatic conditions, and some regions were more efficient than others as a result. This advocates a site-specific approach and a potential prioritization of regions according to their production and life cycle performance potentials.

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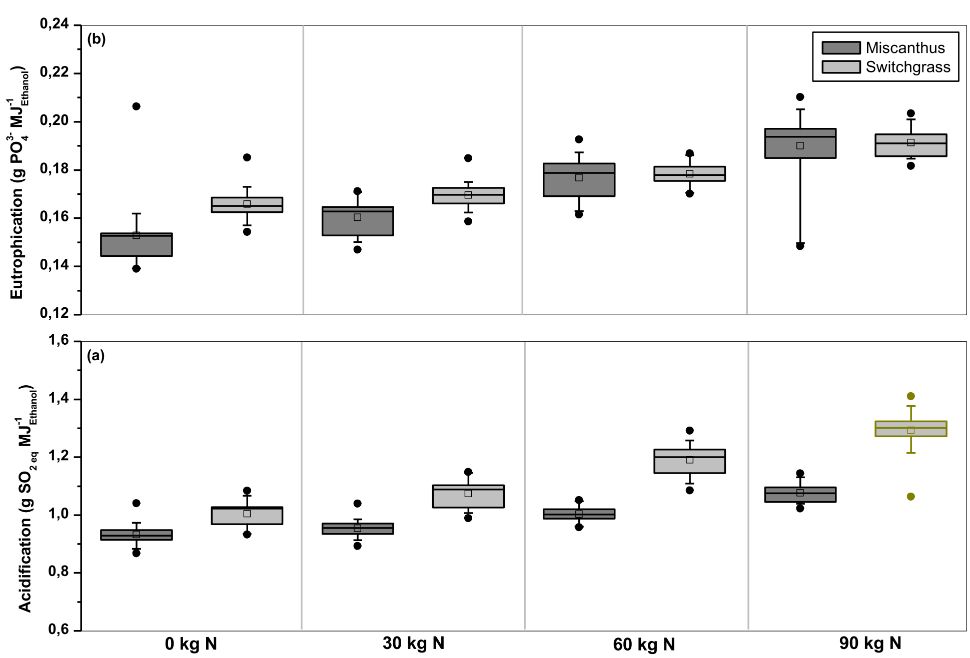

Fig. 6. Boxplots of regional terrestrial acidification potentials for miscanthus- and switchgrass-based ethanol in France, as a function of fertilizer N input rates.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Sylvestre Njakou Djomo reports financial support was provided by European Commission. No other activities to declare

Data availability

Data will be made available on request.

Acknowledgments

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.clcb.2023.100059.

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