



Legacy effects of individual crops affect N₂O emissions accounting within crop rotations

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Abstract

Uruguay is pursuing renewable energy production pathways using feedstocks from its agricultural sector to supply transportation fuels, among them ethanol produced from commercial technologies that use sweet and grain sorghum. However, the environmental performance of the fuel is not known. We investigate the life cycle environmental and cost performance of these two major agricultural crops used to produce ethanol that have begun commercial production and are poised to grow to meet national energy targets for replacing gasoline. Using both attributional and consequential life cycle assessment (LCA) frameworks for system boundaries to quantify the carbon intensity, and engineering cost analysis to estimate the unit production cost of ethanol from grain and sweet sorghum, we determined abatement costs. We found 1) an accounting error in estimating N₂O emissions for a specific crop in multiple crop rotations when using Intergovernmental Panel on Climate Change (IPCC) Tier 1 methods within an attributional LCA framework, due to N legacy effects; 2) choice of baseline and crop identity in multiple crop rotations evaluated within the consequential LCA framework both affect the global warming intensity (GWI) of ethanol; and 3) although abatement costs for ethanol from grain sorghum are positive and from sweet sorghum they are negative, both grain and sweet sorghum pathways have a high potential for reducing transport fuel GWI by more than 50% relative to gasoline, and are within the ranges targeted by the US renewable transportation fuel policies.

Keywords: attributional LCA, bioenergy, consequential LCA, ethanol, grain sorghum, greenhouse gas emissions accounting, life cycle assessment, nitrous oxide, soil carbon, sweet sorghum

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Introduction

There has been much interest over the last decade in developing and scaling renewable energy to address both climate change and energy security in countries around the world (Kammen, 2006). Rationale for developing renewable energy varies by country and economy, but a strong case for building domestic supply capacity is to support rural economic development. Policies for pursuing renewable energy for decarbonizing transportation favor the development of domestic commercial biofuels as these also help to invest in local economies and reduce trade deficits related to foreign oil dependence. In North America, these policies have

been designed to follow life cycle assessment (LCA)-based greenhouse gas (GHG) accounting (U.S. Congress 2007; US EPA 2010). Countries around the world are developing similar policies in an effort to spur their local economies, and in some cases, also to mitigate climate change. In Uruguay, domestic biofuels are in production and are poised to expand production of domestic energy resources. Uruguay's government-owned oil company, ANCAP, has invested in domestic production of ethanol from sorghum crops, but to this point, they have not evaluated the climate impacts of their biofuel program. Our goal was to develop a life cycle framework to evaluate their current biofuels from sorghum, using this system approach to inform policy to understand and guide the life cycle performance of Uruguay's domestic biofuel investment using metrics such as GHG accounting.

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Energy is an important driver for economic growth, and for many developing nations, its consumption is projected to increase to improve standards of living. In Uruguay, demand for energy has increased 70% over the last 10 years, with the industrial sector being the highest consumer (~76 PJ), followed by the transportation (49 PJ) and residential and commercial (46 PJ) sectors (DNE, 2013). Near-term options for meeting energy demand have been met by increased import of petroleum and a small, but expected to increase in import of natural gas since Uruguay lacks domestic reserves of fossil energy resources. There are no reserves of coal, petroleum, or natural gas, and thus, historically any use of such resources for thermal, electrical, and transportation has relied on import from the global market. In 2013, fossil energy accounted for 41% of energy consumed, 40% of this was comprised of petroleum, and 1% natural gas, while renewable energy accounted for 59% of energy consumed, with 39% coming from waste, 33% hydroelectric power, 19% from wood, 6% from wind, and 3% from biofuels. The transportation sector, almost exclusively dependent on liquid fuel supply, largely relies on diesel and gasoline refined from imported crude oil, with some domestic production of fuel ethanol and biodiesel from domestic agricultural products accounting for ~1.5% of total energy (DNE (Dirección Nacional de Energía), 2013). Biomass from forest and agricultural sectors is an important source of renewable energy to support effort to address climate change. Near-term energy policy in Uruguay is focusing on developing liquid fuel markets from agricultural feedstocks and electricity from forest biomass, which have been shown to reduce GHGs associated with energy production and use (Adler *et al.*, 2012).

LCA approaches are being pursued to best guide decisions in both energy sectors; GHG accounting and cost abatement (e.g., Pourhashem *et al.*, 2013) are valuable metrics to help understand the effectiveness of policy investments, in particular when government is investing in carbon abatement strategies. Transportation fuel supply must be compatible with the vehicle fleet and new vehicles entering the market. Thus, ethanol-blended fuels can be scaled up to the blend wall for the existing fleet of gasoline-fueled vehicles and up to 85% for flexible fuel vehicles.

Policy around low-carbon transportation fuels in the United States (CARB 2010; US EPA 2010) uses a combination of attributional LCA (ALCA) (ISO 2006) and consequential LCA (CLCA) (Ekvall & Weidema, 2004) methods, the latter being used primarily to quantify carbon emissions from indirect land-use change induced by changes in commodity markets (Searchinger *et al.*, 2008; Plevin *et al.*, 2015). CLCA is also used to guide system boundary rules that test a new product or

production strategy against a conventional (baseline) product or production strategy. For example, Sarkara & Miller (2014) used CLCA boundary rules for assessing changes in water quality when introducing switchgrass into agricultural landscapes for bioenergy production. Similarly, both Pourhashem *et al.* (2013) and Adler *et al.* (2015) used CLCA boundary settings to test the effects of soil carbon management within biofuel systems and use these settings to estimate the soil GHG emissions of nitrous oxide and soil carbon change.

Plevin *et al.* (2014) argue that ALCA fails to account for the critical changes within the economy that may result from implementing climate change policy, especially for biofuels. These changes can lead to error when comparing the global warming intensity (GWI) of a biofuel relative to the fossil fuels they aim to displace. The authors conclude that although CLCA can account for change, it also introduces results that are scenario dependent and uncertain when used to evaluate biofuel policy.

In addition to scenarios which define how cropping systems may change with the introduction of a bioenergy crop, there is also the interaction of crops within a rotation which can affect the GHG emissions for a given crop within both the ALCA and CLCA frameworks. In this analysis of bioenergy production in Uruguay, there is not only the increase in planting of grain and sweet sorghum, but the change in crop identity in the rotation due to external economic and regional factors.

Soil biogeochemical changes across crop rotations leading to GHG emissions of N₂O and CO₂ from soils are not always precisely captured when using CLCA or ALCA due to limitations in the estimation methods used. The Intergovernmental Panel on Climate Change (IPCC) has developed guidelines to estimate N₂O emissions from cropped and grazed soils, as well as soil organic carbon (SOC) stock changes (de Klein *et al.*, 2006). Explicit in the guidelines are tiers reflecting methodological complexity with Tier 1 methods based on default emission factors being the simplest, Tier 3 methods employing the complex process-based models, and Tier 2 methods being intermediate. Process-based models (Tier 3) have matched measured N₂O emissions more closely (Del Grosso *et al.*, 2008) and represented soil carbon changes better (Del Grosso *et al.* 2016) than IPCC Tier 1 methods. Furthermore, as hypothesized in this study, when considering complex rotations, Tier 1 methods do not capture legacy effects of nitrogen management from prior crops in a rotation because they assume that all applied N is cycled within a year. This could lead to underestimates of N₂O emissions with Tier 1 methods due to carryover of N from one crop in a rotation to another, a source of N not accounted for in Tier 1 in contrast with Tier 3 N₂O estimation methods.

Given the challenge of appropriately capturing changes in agricultural GHG emissions when a biofuel policy and the crops that meet the policy are introduced, and the potentially divergent estimation outcomes from Tier 1 and Tier 3 soil GHG accounting, our objective in this article was to evaluate the GWI of newly introduced biofuel pathways in Uruguay's varied agricultural crop rotations using Tier 1 and 3 approaches and CLCA and ALCA frameworks. We explore major differences in direct GHG emissions for biofuels introduced into complex agricultural rotations and posit that decision outcomes from life cycle inventories defined by CLCA and ALCA frameworks can lead to very significant soil N₂O accounting omissions, which will impact how the biofuel program ranks and rates petroleum alternatives. While CLCA encompasses a wide spectrum of changes introduced by a new product or policy, including especially economic effects resulting from market changes (Anex & Lifset, 2014; Hertwich, 2014; Plevin *et al.*, 2014; Suh & Yang, 2014), our goal was to investigate only biophysical changes in soil N₂O emissions resulting from the introduction of a crop within a multicrop system using CLCA because it is not possible to capture such effects with ALCA methods used in prior literature (e.g., Spatari and MacLean 2010). We combine GHG accounting with cost analysis to investigate the abatement cost of future bioenergy supply in Uruguay and evaluate the environmental and cost effectiveness of their major investments into grain sorghum and sweet sorghum biorefinery capacity. The analysis aims to explore the range of differences in biofuel life cycle GWI when using consequential and attributional system boundaries, IPCC Tier 1 and Tier 3 approaches to estimate soil GHG emissions, and agricultural rotations scenarios that include and exclude pasture land, which constitutes a major fraction of agricultural land in Uruguay.

Materials and methods

Site selection and description

Our analysis focused on two locations in Uruguay where ethanol is being produced from agricultural feedstock, Paysandú in western and Bella Unión in northern Uruguay (Fig. 1). The site near Paysandú produces ~70 000 m³ ethanol annually from grain sorghum, requiring 156 600 Mg of grain sorghum annually (Table 1). With the regional average grain sorghum yield of ~4 Mg ha⁻¹, the biorefinery requires ~40 000 ha of land annually. The site near Bella Unión produces ethanol from sugarcane and sweet sorghum. They have an annual production capacity of ~30 000 m³ ethanol annually, ~95% from sugarcane, and ~5% from sweet sorghum. Although these locations have similar climate without a large gradient across the region (Table 2), different crops are produced in these regions due to

differences in infrastructure, such as distance to ports, and sugarcane mills in the north. The cropland in Paysandú is more dominated by grain crops, whereas in Bella Unión, commodity crops are less common, and forage crops more common.

Life cycle assessment

The life cycle assessment (LCA) was conducted in two phases as prescribed by ISO 14040 (2006) procedures. First, all sources of greenhouse gases were tabulated in a life cycle inventory (LCI) analysis and then the contribution of the sources of greenhouse gases on climate was determined by converting the inventory to CO₂ equivalents (life cycle impact assessment, LCIA).

The DayCent model was used to quantify changes in soil organic carbon (SOC), N₂O emissions, and NO₃ leaching over the crop production cycle. The DayCent biogeochemical emissions were incorporated into the life cycle inventory (LCI) model (Adler *et al.*, 2007, 2012).

DayCent model description. The DayCent biogeochemical model (Parton *et al.*, 1998; Del Grosso *et al.*, 2001), a daily time-step version of the CENTURY model (Parton *et al.*, 1994), was used to estimate crop yields and evaluate changes in soil organic carbon (SOC) and soil N₂O emissions for the LCA. Using daily weather, soil-texture class, and land-use inputs, DayCent simulates crop production, soil organic-matter (SOM) transformations, soil water and temperature dynamics, trace-gas fluxes, and other ecosystem processes. Plant growth is controlled by nutrient and water availability, temperature, and cultivar-specific characteristics such as phenology, N concentration of biomass components, and maximum growth rate. SOM dynamics are a function of the quantity and quality of biomass inputs, water, temperature and nutrient limitation, tillage intensity, and soil properties related to texture. The model simulates soil N₂O emissions from nitrification and denitrification, as well as CH₄ oxidation in drained soils. The ability of DayCent to simulate NPP, SOC stock changes, N₂O emissions, and NO₃ leaching has been tested with data from various native and managed systems (Del Grosso *et al.*, 2012; US EPA 2013). DayCent has been shown to reliably represent plant growth and GHG fluxes for different biofuel cropping systems, and the model has been successfully applied at the site (Adler *et al.*, 2007) and regional levels (Davis *et al.*, 2012).

Daily weather data for Paysandú and Bella Unión Uruguay required to drive DayCent were acquired from the nearby INIA weather station in Salto Grande (31°S 16' 22", 57°W 53' 27"), ~120 km from both biorefinery locations. Soil texture data representative of the locations were obtained from Altamirano *et al.* (1976). The representative soil in Bella Unión for sweet sorghum was a Typic Hapludert clay soil of the series Itapebi Tres Arboles, while in Paysandú for grain sorghum, it was a Typic Argiudoll clay loam of the series San Manuel. Both soils are common throughout the cropped areas of the Pampean region of Uruguay and Argentina, very productive, high fertility and poorly drained especially the Hapludert, although poor drainage is usually not a limiting factor because these soils are located in rolling landscapes. Soil physical and hydraulic

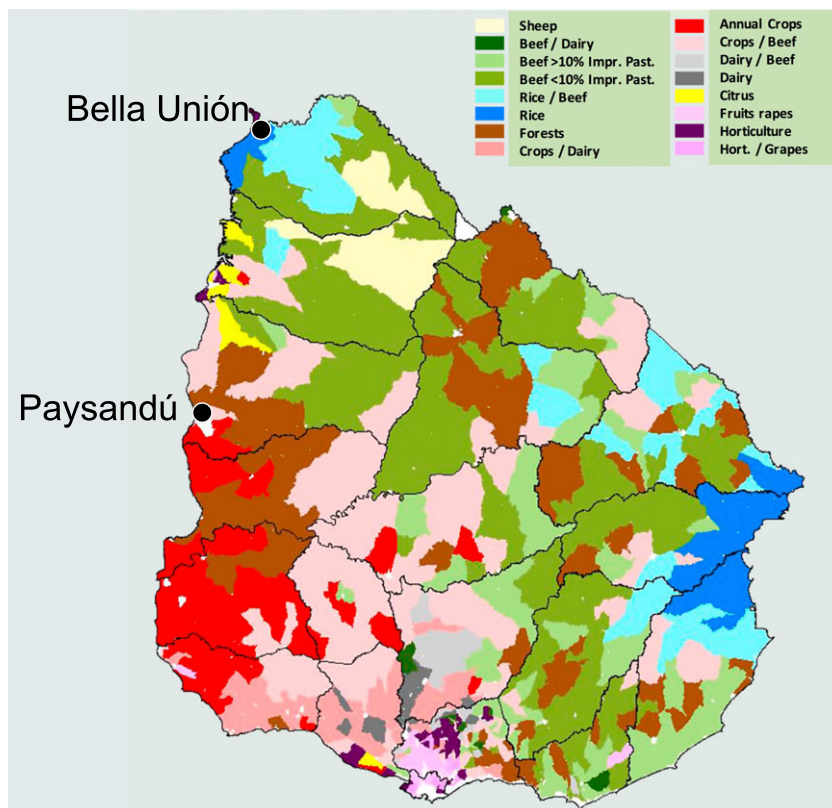


Fig. 1 Description of cropland in Uruguay and location of ethanol biorefineries in Paysandú and Bella Unión (DIEA, MGAP, 2015).

Table 1 Biorefinery feedstock requirements and production capacity

Biorefinery location	Crop	Crop contribution* (%)	Biorefinery capacity† (m ³ yr ha ⁻¹ yr ⁻¹)	Feedstock requirement‡ (Mg yr ha ⁻¹ yr ⁻¹)
Bella Unión	Sweet sorghum	5	30 000	410 000
	Sugarcane	95		
Paysandú	Grain sorghum	100	70 000	156 600

*% of ethanol produced from crop.

†Total ethanol production capacity of biorefinery.

‡Total amount of feedstock required as stalks for sweet sorghum and sugarcane and grain for grain sorghum.

properties needed for model inputs were calculated from texture class and Saxton *et al.*'s (1986) hydraulic properties calculator (available online at <http://www.bsyste.wsu.edu/saxton/soilwater>).

Model outputs are sensitive to current SOC levels, which in turn are influenced by previous vegetation cover and land management. To acquire reasonable modern SOC levels, about 1950 years of native vegetation followed by plowing and about 60 years of cropping were simulated. Plow out of native grazed grasslands was assumed to occur in the year 1951. Historically accurate cropping systems were simulated, and improved cultivars, fertilizer applications, and tillage intensity were introduced at appropriate times. From 1952 to 1975, corn–wheat rotations were common, no N fertilizer was applied, and conventional tillage was used. From 1976 to 2007, soybean was

introduced and included in the corn–wheat rotations and N fertilizer applied; in response to soil degradation, pasture was included in the crop rotation and no-tillage was adopted (García-Préach *et al.*, 2004).

DayCent model simulations. Simulations of changes in soil N₂O emissions and SOC fluxes using DayCent were performed for the following crops: grain sorghum [*Sorghum bicolor* (L.) Moench], oat [*Avena sativa* L.], pasture, ryegrass [*Lolium* L.], sweet sorghum [*Sorghum bicolor* (L.) Moench], soybeans (*Glycine max* Merr.), and winter wheat (*Triticum aestivum* L.). The pastures contain a mixture of grasses (fescue, ryegrass) and legumes (white clover, red clover, sometimes alfalfa) with a low C/N ratio. The modeled rotations were developed by regional experts and are described in Table 3. They include a

Table 2 Description of the crop production sites simulated with the DayCent biogeochemical model in Uruguay

Crop	MAP (mm)	MAT (°C)	Soil texture	GDD	Tillage*
Sweet sorghum	1424	18.7	Clay	6007	No till
Grain sorghum	1424	18.7	Clay loam	6007	No till

Notes: Key to abbreviations: MAP, mean annual precipitation; MAT, mean annual temperature; GDD, growing degree days.

*Type of tillage prior to crop establishment.

baseline rotation which describes a typical crop rotation prior to expansion of bioenergy crop production in the area, and a paired bioenergy crop rotation. Both the baseline and bioenergy crop rotations included scenarios with and without a three-year pasture component, for both grain and sweet sorghum. The grain sorghum scenario without pasture and the sweet sorghum scenario with pasture would probably be more typical for the regions, but a change in commodity prices could move rotations toward or away from increased grain or pasture in the rotation.

DayCent simulations were run for 36 years following initiation of these rotations. Outputs for carbon (C) and nitrogen (N) fluxes between the atmosphere, vegetation, and soil were then used as inputs into the crop production LCI model to estimate the global warming intensity (GWI) of feedstocks for energy use (Adler *et al.*, 2012). The direct N₂O was the mean annual N₂O emissions over the simulation period. To calculate indirect N₂O, we combined DayCent outputs for NO₃ leached and N volatilized with IPCC (de Klein *et al.*, 2006) methodology. IPCC (de Klein *et al.*, 2006) methodology assumes that 0.75% of NO₃-N leached is eventually denitrified to N₂O-N in water ways and that 1% of volatilized N (NO_x + NH₃) is deposited on soil and converted to N₂O. N₂O emissions were converted to CO₂e by assuming that its global warming potential is 298 times that of CO₂ on a mass basis (Forster *et al.*, 2007).

IPCC Tier 1 greenhouse gas estimations. The Tier 1 method for soil N₂O emissions assumes that fixed portions of N additions to soil from fertilizer, manure, and crop residues not removed during harvest operations are converted to direct and indirect emissions. We used the default direct N₂O factor of 1% for synthetic fertilizer and crop residues for the cropped portion of the rotations and the default 2% for manure deposited by grazing animals during the pasture portion of the rotations. We also used the default indirect factors from IPCC (de Klein *et al.*, 2006) and summed to obtain total N₂O emissions. For SOC stock changes, the Tier 1 method estimated an initial SOC stock of 8800 g C m⁻² given the soil types and climate for the sites in Uruguay. We then applied the default SOC stock change factors based on land-use change as described in IPCC (de Klein *et al.*, 2006) and calculated annual SOC changes by assuming that SOC stocks would obtain equilibrium after 20 years of consistent land use.

Description of LCI and LCIA. DayCent output data on changes in SOC and N₂O were combined with a life cycle inventory (LCI) model for the selected biomass feedstocks converted to ethanol. Crop yield output from DayCent was expressed as g C m⁻² yr⁻¹ and converted to MJ ha⁻¹ assuming biomass feedstock was 43.5% carbon (Brown, 2003), ethanol yield was 442 and 216 L ethanol Mg⁻¹ feedstock for grain and sweet sorghum, respectively (Table 4). The lower heating value of ethanol (21.2 MJ L⁻¹) was used for all life cycle calculations. The LCI model follows ISO 14040 (2006) procedures and includes the fuel production (feedstock production, transport, fuel conversion, fuel distribution) and use (combustion) cycles (Fig. 2). Life cycle GHG emissions include transportation and field application of nutrients and farming operations specific to the crop rotation. Coproducts compared among the ethanol pathways were treated using system expansion crediting (ISO, 2006) and those credits depended on the rotation. For example, in the case of grain sorghum, the distillers dried grains and solubles (DDGS) coproduct was assumed to displace soybean meal on the market similar to other DDGS coproducts derived from starch-based dry grind processes. In the case of sweet sorghum, the annual production of surplus electricity (1452 MWh)

Table 3 Description of crop rotations simulated with DayCent

Crop	Rotation	Year 1		Year 2		Year 3	
		Winter	Summer	Winter	Summer	Winter	Summer
Sweet sorghum	Baseline*	Oat	Soybean	Ryegrass	Grain sorghum	Ryegrass	Soybean
	Sans pasture	Oat	Sweet sorghum	Ryegrass	Sweet sorghum	Ryegrass	Soybean
	Baseline†‡	Oat	Soybean	Ryegrass	Grain sorghum	Ryegrass	Soybean
	Pasture‡	Oat	Sweet sorghum	Ryegrass	Sweet sorghum	Ryegrass	Soybean
Grain sorghum	Baseline*	Wheat	Soybean	Wheat	Soybean	Ryegrass	Soybean
	Sans pasture	Wheat	Soybean	Wheat	Grain sorghum	Ryegrass	Soybean
	Baseline†‡	Wheat	Soybean	Wheat	Soybean	Ryegrass	Soybean
	Pasture‡	Wheat	Soybean	Wheat	Grain sorghum	Ryegrass	Soybean

*Baseline sans pasture.

†Baseline pasture.

‡The first three years of the rotation are followed by three years of pasture.

produced was assumed sold to Uruguay's electricity market and would displace marginal fuel sources for electricity within the existing electricity mixture, which consist of fuel oil that is used on top of hydroelectric and biomass sources of baseload power. Life cycle impact assessment (LCIA) was undertaken following ISO 14040 (2006) standards to estimate the GWI of the ethanol produced and compared to the GWI of gasoline (93 g CO₂e MJ⁻¹) as documented by US EPA (2010) and includes end use in a light-duty internal combustion vehicle. The GWI of feedstock production was calculated using 2007 IPCC 100a weighting factors for the individual greenhouse gases (Forster *et al.*, 2007) and summed over the cradle-to-farm-gate life cycle. The LCI model for ethanol produced from grain and sweet sorghum was constructed using SimaPro 8 software (PRé 2015) using existing datasets for select agricultural operations (e.g., feedstock harvest, nutrient replacement)

Development Bank 2015). Operating variable costs and fixed variable costs (labor, general overhead, maintenance, and insurance and taxes) were estimated using data from Gnansounou *et al.* (2005) and scaled to the Bella Union capacity of 30 000 Mg yr⁻¹ sorghum feed. All costs were assumed to be in 2015 US\$. A sensitivity analysis on costs was performed to estimate the range of ethanol unit production costs and used for the abatement cost calculation. Tables S3 and S4 in the Supporting Information summarize the production cost and sensitivity analysis parameter settings for ethanol production from grain sorghum and sweet sorghum, respectively.

Abatement costs. We estimated the GHG abatement cost of grain and sweet sorghum ethanol pathways relative to gasoline using Eqn 1 and included low and high ranges to evaluate cost sensitivity.

$$\text{GHG abatement cost} = - \left[\frac{\text{Unit production cost of ethanol} - \text{Unit production cost gasoline}}{\text{Unit GWI ethanol} - \text{Unit GWI gasoline}} \right] \quad (1)$$

that were parameterized with data collected in Uruguay, and biorefinery operations data from Uruguayan industry (Alur and ANCAP), supplemented with data from literature (e.g., Gnansounou *et al.*, 2005; Nghiem *et al.* 2011) that were parameterized for biorefinery scales in Uruguay. Life cycle GWI contributions from crop production, biorefinery operations, transportation, and vehicle in-use emissions for 100% ethanol produced from sweet sorghum (Table S1) and grain sorghum (Table S2) are in the Supporting Information.

Description of cost and GHG abatement analysis

To test the performance of abating GHGs through introducing grain and sweet sorghum into Uruguay's transport fuel market, the majority of which is owned by the Uruguayan government, we calculated the GHG abatement costs for displacing gasoline.

Production costs. We estimated the unit production cost of ethanol from grain and sweet sorghum. For grain sorghum to ethanol, costs included the capital investment of \$180 million, depreciated over 10 years using straight line depreciation; feedstock and operating variable costs; and fixed variable costs (labor, general overhead, maintenance, and insurance and taxes) using data for corn dry grind facilities (Iowa State University 2015). Grain sorghum feedstock costs were taken from 2015 commodity prices (USDA-NASS 2015).

The cost of producing sweet sorghum to ethanol did not include depreciated capital equipment because existing facilities from the Bella Union sugarcane processing plant are used. The feedstock production cost in Uruguay was calculated to be \$1143 ha⁻¹, which is slightly higher than costs reported for U.S. production in Texas, \$712 ha⁻¹ (Amosson *et al.*, 2011), and North Carolina, \$1023 ha⁻¹ (Veal *et al.*, 2014), and the cost of transporting the feedstock to the biorefinery was estimated to be \$7.70 Mg⁻¹, assuming a transportation distance of 70 km and freight transportation cost of \$0.11 Mg-km⁻¹ (Inter-American

Data on the assumed average, low, and high costs for grain sorghum to ethanol and sweet sorghum to ethanol are summarized in the Supporting Information Tables S1 and S2. The average wholesale price of gasoline by refiners from January 2013 to June 2015 from (EIA 2015) was used (\$0.56 L⁻¹; \$20.64 GJ⁻¹), and the GWI for gasoline was assumed to be 93 g CO₂e MJ⁻¹ (US EPA 2010).

Results

Crop yields and available crop residue

Grain and sweet sorghum yields were similar in both rotations with and without pasture (Table 4). Although the ethanol yields were more than double per unit yield for grain sorghum, dry wt. yields (stem vs. grain) were more than 2.5 times greater for sweet sorghum; the resulting ethanol yields per hectare were >20% higher for sweet sorghum.

Greenhouse gas emissions and nitrogen dynamics

Greenhouse gas emissions varied with both crop and rotation (Table 5). Total N₂O emissions were higher than the baseline for both sweet and grain sorghum; a small reduction in nitrate leaching led to lower indirect N₂O emissions, but these were small relative to direct N₂O emissions. The change in both N₂O emissions and soil carbon were lower for both the sweet and grain sorghum rotation with pasture relative to the rotation without pasture.

Cumulative N₂O emissions varied with crop and rotation. There was a legacy effect following the pasture, whether that period was fallow (Fig. 3) or had crops

Table 4 Crop plant and ethanol yield (dry wt. basis) over 36-year DayCent simulation period. Values are means with standard error in parentheses

Crop	Rotation	Yield* (Mg ha ⁻¹)	Biomass† (Mg ha ⁻¹)	Crop residue‡ (Mg ha ⁻¹)	Ethanol yield§ (L Mg ⁻¹)	Ethanol yield§ (L ha ⁻¹)
Sweet sorghum	Sans pasture	10.28	16.83 (0.23)	6.55	216	2225
	Pasture	10.29	16.85 (0.82)	6.55	216	2228
Grain sorghum	Sans pasture	4.07 (0.31)	8.15	4.07	442	1802
	Pasture	4.04 (0.47)	8.08	4.04	442	1786

*DayCent simulated crop yields, both grain (grain sorghum) and stem (sweet sorghum) yields are expressed as dry wt. Stem yields were about 75% of total biomass; grain, leaves, and 16.7% of stems for sweet sorghum were returned to the soil at harvest as occurs in commercial operations.

†Sweet and grain sorghum biomass included stems, leaves, and grain.

‡Amount of biomass returned to the soil with harvest.

§Ethanol yields are expressed on a dry wt. basis.

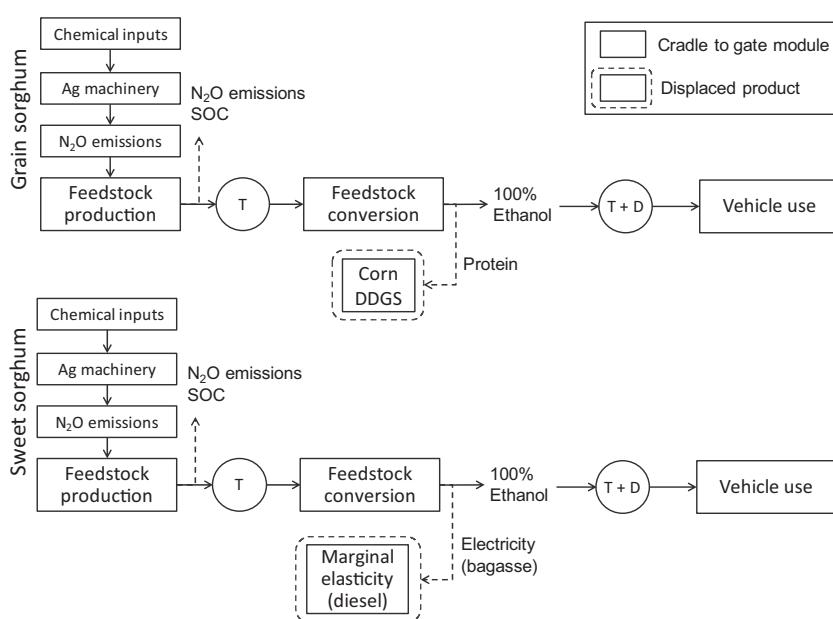


Fig. 2 System boundary for Uruguay's sorghum-to-ethanol pathways. Abbreviations: transportation (T); distribution (D); chemical inputs included GHG emissions associated with production of both fertilizers and pesticides; Ag machinery included GHG emissions associated with fuel use from tillage, planting, chemical application, and harvest; N₂O emissions were from soil and were always positive in contrast to SOC (soil organic carbon) which increased or decreased depending on the rotation.

planted (Fig. 4), N₂O emissions were higher. The effect of pasture on the intensity of N₂O emissions following pasture increased with proximity; N₂O emission intensity was higher for oats and wheat which were nearer in time to pasture than sweet sorghum or soybeans, but were still higher for these crops in rotations with pasture.

Nitrogen inputs and outputs varied between grain and sweet sorghum and the presence of pasture in the rotation (Table 6). More N fertilizer was added to the grain sorghum rotation, whereas N fixation varied with the presence of pasture and frequency of soybean in the rotation. However, both N mineralization and manure/urine

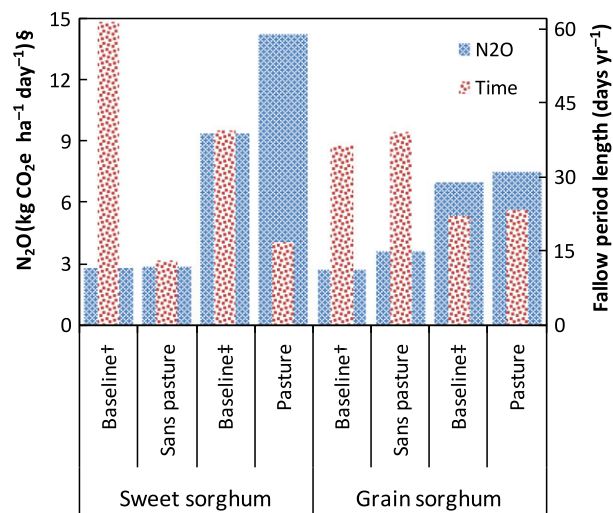
inputs were highest in rotations with pasture. Nitrogen output was highest in rotations with grain sorghum, while grazed N and gaseous N losses were highest in rotations with pasture. Pastures were an important source of internally cycled N leading to large difference in net N input.

Greenhouse gas emissions on a life cycle basis

Both the direction of change between the rotations and quantity varied within and between ALCA and CLCA methods for Tier 1 and Tier 3 methods. Using ALCA methods, Tier 3 N₂O emission estimates were higher

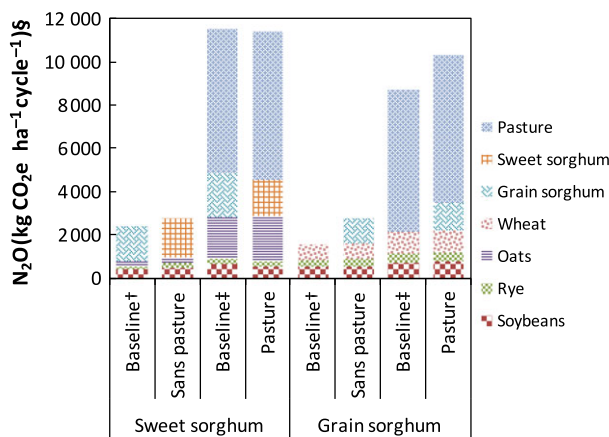
Table 5 Annual changes in soil nitrogen and carbon dynamics influenced by sorghum crop rotation compared with baseline without sorghum. Values are means with standard error in parentheses

Crop	Rotation	Direct N ₂ O	Indirect N ₂ O	Total N ₂ O	Soil organic	Leached N	Mineralized	Soil organic
		(kg CO ₂ e ha ⁻¹ yr ⁻¹)	(kg CO ₂ e ha ⁻¹ yr ⁻¹)	(kg CO ₂ e ha ⁻¹ yr ⁻¹)	(kg C ha ⁻¹ yr ⁻¹)	(kg N ha ⁻¹ yr ⁻¹)	N (kg N ha ⁻¹ yr ⁻¹)	N (kg N ha ⁻¹ yr ⁻¹)
Sweet sorghum	Sans pasture	464 (65)	-18 (3)	447 (66)	109 (35)	-0.5 (0.1)	25.2 (3.8)	8.7 (2.3)
	Pasture	18 (54)	-13.2 (4)	5 (57)	8 (40)	-1.2 (0.3)	10.7 (2.2)	90 (6.6)
Grain sorghum	Sans pasture	303 (37)	14 (3)	317 (39)	52 (9)	4.4 (1.3)	-16.2 (6.1)	6.2 (3.1)
	Pasture	184 (33)	12 (5)	196 (36)	27 (14)	3.1 (1.5)	-6.4 (6.3)	89.3 (5.9)

**Fig. 3** Fallow period direct N₂O emissions and duration. Baseline sans pasture (†); baseline pasture (‡); direct N₂O emissions (kg CO₂e ha⁻¹ day⁻¹) from DayCent (§).

than Tier 1, ~1.7 to >2.3 times higher for sweet sorghum and ~1.5 to 1.65 times higher for grain sorghum (Table 7). While N₂O emissions were similar between rotations within both Tier 1 and Tier 3 methods for grain sorghum, for sweet sorghum, they were lower with pasture for both Tier 1 and Tier 3 methods. ALCA methods only consider N₂O emissions during the growth of the target crop (i.e., grain and sweet sorghum), in contrast to CLCA which considers change. With CLCA methods considering the change from a baseline, for grain sorghum N₂O emissions increased with pasture in the rotation, while for sweet sorghum N₂O emissions decreased, and Tier 3 were higher than Tier 1 estimates (Table 7).

All crop rotation scenarios produced ethanol with a lower GWI than gasoline (Table 8). Using ALCA methods, GWI estimates for Tier 3 were higher than Tier 1, while using CLCA methods, they tended to be lower. All but three crop rotation scenarios reduced the GWI by more than 50% compared with gasoline, and the

**Fig. 4** Total direct N₂O emissions during crop production. Baseline sans pasture (†); baseline pasture (‡); direct N₂O emissions (kg CO₂e ha⁻¹ cycle⁻¹) from DayCent; emissions are averaged over the length of a rotation cycle (§).

three exceptions still reduced the GWI by more than ~40%. Sweet sorghum mostly had a lower GWI than grain sorghum using CLCA but higher using ALCA methods.

GHG abatement costs

On a life cycle basis, all sugar/starch crops for ethanol production maintain a low life cycle GWI largely due to the already low GWI of Uruguay's electricity grid, which is comprised of on average 50% renewable/low-carbon energy (Fig. 5). In particular, the sweet sorghum pathways, whether assessed using consequential or attributional frameworks had consistently lower life cycle GWI compared to grain sorghum pathways. Moreover, the cost estimates (Tables S3 and S4) show that grain sorghum-to-ethanol unit costs (\$32.70 GJ⁻¹ +36%/-14%) are also higher than those of sweet sorghum to ethanol (\$19.60 GJ⁻¹ +11%/-64%), which is marginally lower than that of gasoline (\$20.70 GJ⁻¹; \$0.67 L⁻¹ gasoline). This higher cost the grain sorghum-to-ethanol process is largely due to the capital equipment costs of the

Table 6 Annual quantity and sources of nitrogen inputs and outputs in crop rotations

		N inputs						
		Fertilizer N	Fixed N	Total external N	Mineralized N	Manure/urine N	Total internal N	Total N
Crop	Crop rotation	kg N ha ⁻¹ yr ⁻¹						
Sweet sorghum	Baseline	30.0	125.1	155.1	103.3	0.0	103.3	258.5
	Sans pasture	66.7	65.3	131.9	128.5	0.0	128.5	260.4
Grain sorghum	Baseline	27.7	130.3	158.0	192.2	109.4	301.6	459.6
	Pasture	29.3	106.2	135.5	202.9	110.3	313.3	448.8
Sweet sorghum	Baseline	66.7	109.0	175.7	130.3	0.0	130.3	305.9
	Sans pasture	96.7	76.9	173.6	114.0	0.0	114.0	287.6
	Baseline	36.0	93.0	129.0	242.2	141.4	383.7	512.7
	Pasture	51.0	75.4	126.4	235.8	144.6	380.5	506.8

		N outputs							
		Grain N	Straw N	Grazed N	Gaseous N	Leached N	Total N	Net N input*	Net N input†
Crop	Crop rotation	kg N ha ⁻¹ yr ⁻¹							
Sweet sorghum	Baseline	112.8	0.0	0.0	36.4	1.2	150.4	4.7	108.1
	Sans pasture	49.5	52.4	0.0	37.3	0.7	140.0	-8.0	120.4
	Baseline	62.6	0.0	128.7	82.4	4.5	278.2	-120.2	181.5
	Pasture	26.9	27.8	129.8	78.7	3.3	266.6	-131.1	182.2
Grain sorghum	Baseline	172.9	0.0	0.0	16.9	8.8	198.6	-23.0	107.3
	Sans pasture	159.3	0.0	0.0	17.8	13.2	190.3	-16.7	97.3
	Baseline	91.2	0.0	166.4	41.3	12.3	311.2	-182.2	201.5
	Pasture	81.0	0.0	170.2	42.2	15.4	308.9	-182.5	197.9

*Net N input includes total external N input and total N output.

†Net N input includes both total external and internal N inputs and total N outputs.

Table 7 Changes in soil N₂O emissions and soil carbon per unit ethanol produced relative to the baseline of no grain or sweet sorghum

		Tier 1				Tier 3*			
		Direct N ₂ O	Indirect N ₂ O	Total N ₂ O	ΔSoil carbon	Direct N ₂ O	Indirect N ₂ O	Total N ₂ O	ΔSoil carbon
Crop	Crop rotation	g CO ₂ e MJ ⁻¹							
		<i>Attributional LCA</i>							
Sweet sorghum	Sans pasture	27.9	7.9	35.8	—	59.9	0.1	60.0	—
	Pasture	19.2	5.1	24.3	—	56.3	0.4	56.7	—
Grain sorghum	Sans pasture	16.4	4.8	21.2	—	29.0	2.5	31.5	—
	Pasture	16.5	4.8	21.3	—	31.7	3.5	35.2	—
		<i>Consequential LCA</i>							
Sweet sorghum	Sans pasture	10.9	3.3	14.2	0.0	23.8	-0.9	22.8	20.0
	Pasture	4.0	1.0	4.9	0.0	1.8	-1.3	0.5	1.3
Grain sorghum	Sans pasture	5.4	2.3	7.7	18.7	23.4	1.1	24.5	14.6
	Pasture	10.0	3.3	13.3	37.7	28.6	1.9	30.5	15.6

Notes: Attributional LCA, total N₂O emissions during crop production cycle; consequential LCA, the difference in N₂O emissions between crop rotations with the introduction of grain or sweet sorghum compared with the crop rotation if these bioenergy crops had not been grown.

*DayCent simulated crops, N₂O emissions, and soil carbon.

dry grind facility, unlike the sweet sorghum facility, whose capital costs are assumed fully depreciated due to being added to the existing sugarcane facility in Bella

Union (Table 2). When evaluated as substitutes for gasoline, on average, sweet sorghum-to-ethanol results in negative GHG abatement cost as a result of its lower

Table 8 Global warming intensity of ethanol produced from grain and sweet sorghum

Crop	Crop rotation	Attributional LCA		Consequential LCA	
		IPCC Tier 1	IPCC Tier 3*	IPCC Tier 1	IPCC Tier 3*
		g CO ₂ e MJ ⁻¹			
Sweet sorghum	Sans pasture	34.2	58.5	12.6	41.2
	Pasture	19.7	52.0	0.2	-2.9
Grain sorghum	Sans pasture	19.9	30.3	25.1	37.8
	Pasture	20.0	33.9	49.8	44.9
		Δ% [†]			
Sweet sorghum	Sans pasture	-63	-37	-86	-56
	Pasture	-79	-44	-100	-103
Grain sorghum	Sans pasture	-79	-67	-73	-59
	Pasture	-78	-64	-46	-52

Notes: Attributional LCA, total N₂O emissions during crop production cycle; consequential LCA, the difference in N₂O emissions between crop rotations with the introduction of grain or sweet sorghum compared with the crop rotation if these bioenergy crops had not been grown.

*DayCent simulated crops, N₂O emissions and soil carbon.

†The % change in greenhouse gases compared with the baseline of using gasoline to power the car and light truck fleet at 93 g CO₂e MJ⁻¹.

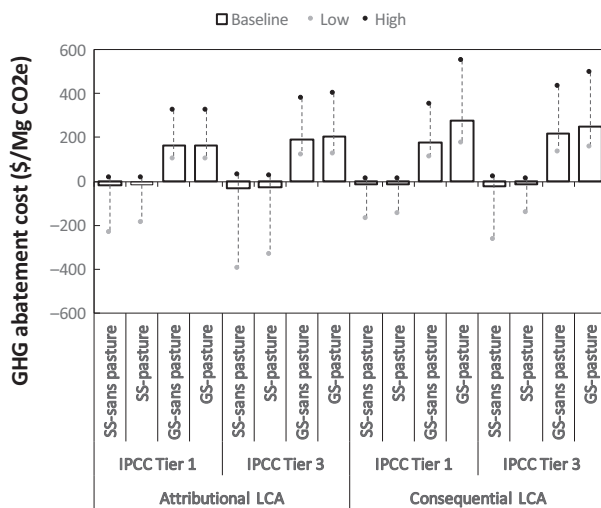


Fig. 5 Greenhouse gas abatement costs for ethanol life cycle pathways derived from sweet sorghum and grain sorghum under different crop rotations using average ethanol production costs. All results are expressed as \$ Mg⁻¹ CO₂e.

GWIs and average and low unit cost relative to gasoline. The production cost of sweet sorghum to ethanol is sensitive to the electricity coproduct selling price (Table S4). When the wholesale electricity selling price is low (\$0.06 kWh⁻¹), the sweet sorghum pathway yields a slightly positive abatement cost. However, when electricity sells at peak price (\$0.24 kWh⁻¹), the facility can sell its coproduct at a higher market price, reducing the marginal production cost of the ethanol product (\$6.97 GJ⁻¹; \$0.15 L⁻¹) and achieving a low negative (cost savings)

GHG abatement cost. Grain sorghum has a positive abatement cost even at the low end of the sensitivity analysis when unit costs are lowest. This is due to the accumulation of amortized capital costs and operating costs, which are not offset enough by revenues from sale of DDGS coproducts to compete with gasoline market prices (\$20.70 GJ⁻¹). Even at high gasoline market prices, which between 2013 and 2015 were up to \$0.80 L⁻¹ (\$24.66), grain sorghum production costs are still higher and result in positive abatement costs.

Discussion

Crop yields and available crop residue

Crop yields can have an important impact on system economics with production scale yield estimates often lower than in small research plot yield trials; we used average commercial field scale yields for the biorefinery in our analysis (Table 4), ~70% of small plot yield trials for sorghum in Uruguay (<http://www.mgap.gub.uy>; <http://www.inia.uy/en>). The modeled grain and sweet sorghum yields are typical of the regions near Paysandú and Bella Unión Uruguay, respectively, where these crops are grown. Farmers using better management on more productive lands could see higher yields, with improved economics and reduced GHG emissions.

The frequency of pasture in grain crop rotations varies with commodity prices, farmer sense of risk, soil conservation regulations, and proximity to the biorefinery and port to reach export markets. Including

pastures in crop rotations can reduce soil erosion and N inputs and losses and increase crop yields and soil carbon (Sanderson *et al.*, 2013; Sulc & Franzluebbers, 2014). In periods of high commodity prices, increased frequency of soybeans and grain sorghum in crop rotations near Paysandú would occur. In contrast, low commodity prices can lead to a shift toward increased pasture. Although pasture may not improve economics relative to grain even during times of low commodity prices, it potentially reduces the risk of crop failure (USDA-NRCS 2004). Consequently, the frequency of grain crops in the rotation would be expected to vary with commodity prices rather than there being an effect of increased bioenergy crop production. In addition to commodity prices, proximity to a good port for export to world grain markets also influences the frequency of grain crops and pasture in the rotation. While Paysandú has good access to a port to reach export markets, Bella Unión is more remote so generally grain crops are more common near Paysandú, while pasture is more common near Bella Unión. Winter double and cover crops are becoming common in Uruguay with wheat more common near Paysandú and oats and ryegrass near Bella Unión. Because increased bioenergy crop production is not expected to affect the frequency of pasture in the rotation, while the frequency of grain commodities is expected to vary for reasons previously described, scenarios with increased pasture and grains in the rotation were evaluated while varying synchronously between the baseline and bioenergy crop rotations.

Greenhouse gas emissions and nitrogen dynamics

The identity of crops in the rotation can have a significant effect on GHG emissions, due to changes in system N with inputs/outputs and changes in crop rotation productivity affecting carbon inputs/outputs. The inclusion of pasture in the rotation had the most significant effect on N₂O emissions both due to changes to N inputs/outputs and residual effects on subsequent crops. Although external N inputs did not appear to be correlated with N₂O emissions, the high internal N cycling from both N mineralization and manure/urine inputs with grazing cattle in pastures did correlate well with N₂O emissions. In spite of N outputs also being higher mainly from N consumed with forage and gaseous N emissions, net N inputs were also higher when internal cycling was included. An important point to note is that a portion of N consumed by grazing cattle is recycled as manure and urine back to the pasture rather than being removed from the system. This model behavior is consistent with observations that nitrification rates and N₂O emissions are often more highly correlated with N turnover rates than with soil ammonium

concentrations (Parton *et al.*, 1996). In a previous Day-Cent simulation based in the USA, we observed that N₂O emissions were correlated with N mineralization in a corn–soybean rotation both with and without winter double crops (Adler *et al.*, 2015).

N₂O emissions varied over the crop rotation cycle due to direct effects of crops, the number of times specific crops were planted in the six-year rotation, and the legacy effects on subsequent crops. To separate the individual effects of crops on cumulative rotation N₂O emissions, we quantified the daily N₂O emissions during the fallow period, as well as the annual duration (Fig. 3) and the N₂O emissions of each crop cycle in the rotations (Fig. 4). N₂O emissions during the fallow period were higher when pasture was in the rotation due to greater intensity of N₂O emissions, especially in the sweet sorghum rotation (Fig. 3). Greater N₂O emissions were not due to a longer fallow period; the fallow period was longer without pasture in the grain sorghum rotation and mixed in the sweet sorghum rotation (Fig. 3). The period following pasture was most affected by its presence in the rotation. N₂O emissions intensity increased by a factor of almost 10 with oats following pasture in the sweet sorghum rotation and ~1.5 with wheat following pasture in the grain sorghum rotation (Fig. 4). The pasture effect on N₂O emissions intensity in wheat may have been muted by it occurring twice in the rotation with the second occurrence following soybeans. The N₂O emissions during the bioenergy crop production period was also affected by the presence of pasture due to the legacy effects, sweet sorghum in the rotation with pasture was about 1.6 times higher, while grain sorghum was only about 1.1 times higher than the rotation without pasture. Other differences in N₂O emission intensity with specific crops were more subtle.

The accounting error, if using Tier 1 rather than Tier 3 accounting methods, was significant in this study for sweet sorghum, where the GWI from total N₂O emissions was >30% lower with pasture when using Tier 1, but similar and only ~5% lower using Tier 3 methods. This occurred due to legacy effects of legumes in the pasture being captured with Tier 3 and not with Tier 1 methods, where the sweet sorghum following pasture had a lower requirement for N fertilizer due to the 'N credit' from the pasture. Although there is a large range of uncertainty around N₂O estimates (Del Grosso *et al.*, 2008), this would not affect the presence of legacy N in multiple crop rotations.

The quantity and quality of carbon inputs from crop residue and roots relative to the previous rotation or the baseline rotation will affect the direction of change in soil carbon. Both with and without pasture in the rotation SOC decreased in sweet sorghum and increased in grain sorghum rotations relative to the baseline

(Table 5). The direction of change in SOC was consistent with C inputs, with C inputs being lower for sweet sorghum and higher for grain sorghum rotations relative to the baseline. Garcia-Préach *et al.* (2004) observed that the soil had a significant effect on the direction of change in soil carbon with pasture in the rotation observing both increases and decreases in SOC.

Greenhouse gas emissions on a life cycle basis

Selection of a baseline rotation for scenario analysis is the most significant factor affecting results when CLCA methods are used and may be the most uncertain component of the LCA, with growing uncertainty expected in factors related to crop rotation and management to be implemented in the future. This aspect is consistent with what Plevin *et al.* (2014) describe regarding scenarios explored through CLCA and is also relevant to cases in ALCA where land use is a dominant factor (Soimakallio *et al.*, 2015). Although regional factors affect the portfolio of crops grown, commodity prices have a significant effect on farmer choices and these are hard to predict from year to year, let alone over a 20–30-year timeframe commonly used in biofuel LCAs. Although economic models are commonly suggested to address this issue (Khanna & Crago, 2012), and those models are suggested as inputs into CLCAs [see Earles & Halog (2011) and Earles *et al.* (2012) for an example application in the forestry sector], their results are driven by underlying assumptions of commodity prices, which also host much uncertainty as a means of representing consequential change, an artifact that is also inherent in the socioeconomic complexity described by Suh & Yang (2014) and Hertwich (2014). In this study, we relied on local agricultural commodity experts to define the rotations and one would not expect economic models to significantly improve the certainty of a baseline choice.

Implications of Tier 1 and 3 GHG estimation with ALCA and CLCA methods

ALCA methods are the most commonly used in GHG LCAs; however, they are not able to capture the change in GHG emissions attributable to bioenergy feedstock demand, an important prerequisite for carbon markets. This gives rise to the need to establish a 'business as usual' scenario without bioenergy feedstocks, and an 'anticipated baseline' counterfactual scenario that incorporates the increased demand for bioenergy feedstock used with CLCA methods. However, baselines required to measure additionality can be highly uncertain, especially when predicting future outcomes. We assumed that bioenergy crops did not affect the presence of pasture in the rotation; that instead rotations were influenced more

by commodity prices and proximity to ports; therefore, the presence of pasture was in synchrony between the baseline and bioenergy crop rotation.

We come to the following conclusions when comparing and contrasting LCA and N₂O estimation methods. First, within an attributional LCA framework, using IPCC Tier 1 methods to estimate N₂O emissions for a single crop within a multiple crop rotation can result in an accounting error because it assumes that residue N cycles completely during that crop year, ignoring legacy effects of residue decomposition between years, which is especially important when the preceding crop is a legume. Legacy effects are greatest immediately following the crop having the effect, in this case pasture with legumes. Therefore, we saw a greater effect on sweet sorghum than grain sorghum when using Tier 1 LCA methods than Tier 3. Second, the choice of baseline and crop identity in rotations evaluated within the CLCA framework both affect the GWI of ethanol. Understanding the uncertainty of the baseline is important when applying CLCA methods and may be more uncertain than IPCC methods for quantifying GHG emissions. Although there is a perception that CLCA methods offer a means of capturing the environmental impacts resulting from changes or introductions of technology or policies, they cannot overcome the uncertainty that comes with modeling unknown future trajectories, including how a 'baseline' is defined, an argument raised by Plevin *et al.* (2014). Not only does the baseline choice affect the GWI, but so can the identity of crops in the rotation due to the legacy effects that can carry over to crops following in the rotation. Finally, ethanol produced from both grain and sweet sorghum reduced the GWI >50% relative to gasoline in >80% of the scenarios (all but three crop rotation scenarios). The U.S.'s national renewable fuel standard classifies advanced fuels, including ethanol fuel made from noncorn feedstocks, as those having a GWI that is at least 50% lower than that of gasoline. While Uruguay's alternative fuel policies aim to incentivize domestic fuel production rather than a carbon reduction target, this analysis shows climate change mitigation benefits from their investment in grain and sweet sorghum processing technology. However, production costs are high for grain sorghum and on average low for sweet sorghum, subject to electricity peak pricing, compared to gasoline. Although the Uruguayan government has specifically not implemented a subsidy (or a carbon tax on gasoline) to recover the shortfall between grain sorghum–alcohol production costs and gasoline, ethanol selling prices in Uruguay have been as high as \$1.80 L⁻¹ (\$85 GJ⁻¹), which allows cost recovery for both sorghum-to-ethanol pathways and in such market conditions renders each negative (cost saving) in GHG cost abatement.

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References

- Adler PR, Del Grosso SJ, Parton WJ (2007) Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. *Ecological Applications*, **17**, 675–691.
- Adler PR, Del Grosso SJ, Inman D, Jenkins RE, Spatari S, Zhang Y (2012) Mitigation opportunities for life cycle greenhouse gas emissions during feedstock production across heterogeneous landscapes. In: *Managing Agricultural Greenhouse Gases: Coordinated Agricultural Research Through GRACEnet to Address Our Changing Climate* (eds Liebig M, Franzluebbers AJ, Follett RF), pp. 203–219. Elsevier Inc., New York, NY.
- Adler PR, Mitchell JG, Pourhashem G, Spatari S, Del Grosso SJ, Parton WJ (2015) Integrating biorefinery and farm biogeochemical cycles offsets fossil energy and mitigates soil carbon losses. *Ecological Applications*, **25**, 1142–1156.
- Altamirano A, Da Silva H, Duran A, Echeverria A, Panario D, Puentes R (1976) *Carta de reconocimiento de suelos del Uruguay*. Tomo III, Clasificación de Suelos. Dirección de Suelos y Fertilizantes. Ministerio de Ganadería, Agricultura y Pesca, Montevideo, Uruguay.
- Amosson S, Girase J, Bean B, Rooney W, Becker J (2011) Economic analysis of sweet sorghum for biofuels production in the Texas high plains. Texas A&M University. Available at: <http://amarillo.tamu.edu/files/2011/05/Sweet-Sorghum.pdf> (accessed 15 September 2015).
- Anex R, Lifset R (2014) Life cycle assessment different models for different purposes. *Journal of Industrial Ecology*, **18**, 321–323, <https://doi.org/10.1111/jiec.12157>.
- Brown RC (2003) *Biorenewable Resources*. Iowa State Univ. Press, Ames.
- CARB (California Air Resources Board) (2010) Subarticle 7. Low Carbon Fuel Standard, Final Rule. Sect. Section 95480.
- Davis SC, Parton WJ, Del Grosso SJ, Keough C, Marx E, Adler PR, DeLucia EH (2012) Impact of second-generation biofuel agriculture on greenhouse-gas emissions in the corn-growing regions of the US. *Frontiers in Ecology and the Environment*, **10**, 69–74.
- Del Grosso SJ, Parton WJ, Mosier AR, Hartman MD, Brenner J, Ojima DS, Schimel DS (2001) Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In: *Modeling Carbon and Nitrogen Dynamics for Soil Management* (eds Schaffer M, Ma L, Hansen S), pp. 303–332. CRC Press, Boca Raton, Florida, USA.
- Del Grosso SJ, Wirth T, Ogle SM, Parton WJ (2008) Estimating agricultural nitrous oxide emissions. *EOS, Transactions American Geophysical Union*, **89**, 529–530.
- Del Grosso SJ, Parton WJ, Adler PR, Davis S, Keogh C, Marx E (2012) DayCent model simulations for estimating soil carbon dynamics and greenhouse gas fluxes from agricultural production systems. In: *Managing Agricultural Greenhouse Gases: Coordinated Agricultural Research Through GRACEnet to Address Our Changing Climate* (eds Liebig M, Franzluebbers AJ, Follett RF), pp. 241–250. Elsevier Inc., New York, NY.
- Del Grosso SJ, Gollany HT, Reyes-Fox M (2016) Simulating soil organic carbon stock changes in agro-ecosystems using CQESTR, DayCent, and IPCC Tier 1 methods. In: *Modeling of Greenhouse Gas Emissions and Carbon Storage in Agricultural and Forest Systems*, (eds Del Grosso SJ, Ahuja L, Parton WJ), pp. 89–110. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, Madison, WI, USA.
- DIEA, MGAP (2015) Regiones agropecuarias del Uruguay. Dirección de Estadística Agropecuarias (DIEA), Ministerio de Ganadería, Agricultura y Pesca, May 2015, Montevideo, Uruguay. <http://www2.mgap.gub.uy/DieaAnterior/regiones/Regiones2015.pdf> (accessed 15 September 2015).
- DNE (Dirección Nacional de Energía) (2013) Balance energético nacional. Ministerio de Industria, Energía y Minería, Montevideo, Uruguay. Available at: <http://www.dne.gub.uy/documents/15386/5631903/1.1%20INFORME%20GENERAL%20BEN2013.pdf> (accessed 15 September 2015).
- Earles JM, Halog A (2011) Consequential life cycle assessment: a review. *International Journal of Life Cycle Assessment*, **16**, 445–453.
- Earles JM, Halog A, Ince P, Skog K (2012) Integrated economic equilibrium and life cycle assessment modeling for policy-based consequential LCA. *Journal of Industrial Ecology*, **17**, 375–384.
- EIA (2015) U.S. Total Gasoline Wholesale/Resale Price by Refiners (Dollars per Gallon). Available at http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMA_EPM0_PWG_NUS_DPG&f=M (15 September 2015).
- Ekvall T, Weidema BP (2004) System boundaries and input data in consequential life cycle inventory analysis. *International Journal of Life Cycle Assessment*, **9**, 161–171.
- Forster P, Ramaswamy V, Artaxo P (2007) Changes in atmospheric constituents and in radiative forcing. In: *Climate Change 2007: The Physical Science Basis* (eds Solomon S et al.), pp. 129–234. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- García-Préchal F, Ernst O, Siri G, Terra JA (2004) Integrating no-till into crop-pasture rotations in Uruguay. *Soil and Tillage Research*, **77**, 1–13.
- Gnansounou E, Dauriat A, Wyman CE (2005) Refining sweet sorghum to ethanol and sugar: economic trade-offs in the context of North China. *Bioresource Technology*, **96**, 985–1002.
- Hertwich E (2014) Understanding the climate mitigation benefits of product systems: comment on “Using attributional life cycle assessment to estimate climate-change mitigation...”. *Journal of Industrial Ecology*, **18**, 464–465.
- Inter-American Development Bank (2015) IDB Regional Observatory for Freight Transport and Logistics, Freight Transport and Logistics Statistics Yearbook. Available at: <http://publications.iadb.org/handle/11319/6885> (accessed 15 September 2015).
- Iowa State University (2015) Historical Ethanol Operating Margins. Iowa State University Center for Agricultural and Rural Development Available at: http://www.card.iastate.edu/research/bio/tools/hist_eth_gm.aspx (15 September 2015).
- ISO 14040 (2006) *Environmental management—Life cycle assessment—Principles and framework*; ISO 14040:2006(E). International Standards Organization, Geneva.
- Kammen DM (2006) The rise of renewable energy. *Scientific American*, **295**, 84–93.
- Khanna M, Crago CL (2012) Measuring indirect land use change with biofuels: Implications for policy. *Annual Review of Resource Economics*, **4**, 161–184.
- de Klein C, Novoa RSA, Ogle S (2006) N₂O emissions from managed soils, and CO₂ emissions from lime and urea application. In: *2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 4: Agriculture, Forestry, and Other Land Use* (eds Eggleston S et al.), pp. 1–54. IGES, Japan.
- Nghiem NP, Ramirez EC, Mcaloon AJ, Yee W, Johnston DB, Hicks KB (2011) Economic analysis of fuel ethanol production from winter hulled barley by the EDGE (Enhanced Dry Grind Enzymatic) process. *Bioresource Technology*, **102**, 6696–6701.
- Parton WJ, Ojima DS, Cole CV, Schimel DS (1994) A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: *Quantitative Modeling of Soil Forming Processes* (eds Bryant RB, Arnold RW), pp. 147–167. Soil Science Society of America, Madison, Wisconsin, USA.
- Parton WJ, Mosier AR, Ojima DS, Valentine DW, Schimel DS, Weier K, Kulmala AE (1996) Generalized model for N₂ and N₂O production from nitrification and denitrification. *Global Biogeochemical Cycles*, **10**, 401–412.
- Parton WJ, Hartman MD, Ojima DS, Schimel DS (1998) DAYCENT and its land surface submodel: description and testing. *Global and Planetary Change*, **19**, 35–48.
- Plevin RJ, Delucchi MA, Creutzig F (2014) Using attributional life cycle assessment to estimate climate-change mitigation benefits misleads policy makers. *Journal of Industrial Ecology*, **18**, 73–83.
- Plevin RJ, Beckman J, Golub AA, Witcover J, O'hare M (2015) Carbon accounting and economic model uncertainty of emissions from biofuels-induced land use change. *Environmental Science & Technology*, **49**, 2656–2664.
- Pourhashem G, Adler PR, McAlloon A, Spatari S (2013) Cost and greenhouse gas emission tradeoffs of alternative uses of lignin for second generation ethanol. *Environmental Research Letters*, **8**, 025021.
- PRé Consultants (2015) SimaPro. Version 8. PRé Consultants, Amersfoort, The Netherlands.

- Sanderson MA, Archer D, Hendrickson J *et al.* (2013) Diversification and ecosystem services for conservation agriculture: outcomes from pastures and integrated crop–livestock systems. *Renewable Agriculture and Food Systems*, **28**, 129–144.
- Sarkara S, Miller SA (2014) Water quality impacts of converting intensively-managed agricultural lands to switchgrass. *Biomass and Bioenergy*, **68**, 32–43.
- Saxton KE, Rawls WJ, Romberger JS, Papendick RI (1986) Estimating generalized soil–water characteristics from texture. *Soil Science Society of America Journal*, **50**, 1031–1036.
- Searchinger T, Heimlich R, Houghton RA *et al.* (2008) Use of U.S. cropland for biofuels increases greenhouse gases through emissions from land-use change. *Science*, **319**, 1238–1240.
- Soimakallio S, Cowie A, Brandão M *et al.* (2015) Attributional life cycle assessment: Is a land-use baseline necessary? *International Journal of Life Cycle Assessment*, **20**, 1364–1375, <https://doi.org/10.1007/s11367-015-0947-y>.
- Spatari S, Maclean HL (2010) Characterizing model uncertainties in the life cycle of lignocellulose-based ethanol fuels. *Environmental Science & Technology*, **44**, 8773–8780.
- Suh S, Yang Y (2014) On the uncanny capabilities of consequential LCA. *International Journal of Life Cycle Assessment*, **19**, 1179–1184, <https://doi.org/10.1007/s11367-014-0739-9>.
- Sulc RM, Franzluebbers AJ (2014) Exploring integrated crop–livestock systems in different ecoregions of the United States. *European Journal of Agronomy*, **57**, 21–30.
- U.S. Congress (2007) Energy Independence and Security Act of 2007. H.R. 6, 110th Congress, First session. U.S. Congress, Washington, DC, USA.
- US EPA (2010) Renewable fuel standard program (RFS2) regulatory impact analysis. EPA-420-R-10e006. Assessment and Standards Division, Office of Transportation and Air Quality, Washington, DC.
- US EPA (2013) *Inventory of U.S. greenhouse gas emissions and sinks: 1990–2011*, report, US EPA, Washington, DC.
- USDA-NASS (National Agriculture Statistics Service) (2015) Available at: http://www.nass.usda.gov/Quick_Stats/ (accessed September 2015).
- USDA-NRCS (Natural Resources Conservation Service) (2004) Sod-based Rotations: A Proven Old Practice to Improve Soil Productivity. Soil Quality–Agronomy

Technical Note 18, Soil Quality Institute, Auburn, AL. 7 pp. Available at http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_053292.pdf (accessed 30 September 2015).

- Veal MW, Chinn MS, Whitfield MB (2014) Sweet sorghum production to support energy and industrial products. North Carolina Cooperative Extension. Available at: <http://content.ces.ncsu.edu/sweet-sorghum-production-to-support-energy-and-industrial-products.pdf> (accessed 15 September 2015).

Supporting Information

Additional Supporting Information may be found online in the supporting information tab for this article:

Table S1 Life cycle GWI for sweet sorghum: Data include all inputs to the production of grain sorghum, with the exception of DayCent estimates of N₂O emissions and SOC change.

Table S2 Life cycle GWI for grain sorghum: Data include all inputs to the production of grain sorghum, with the exception of DayCent estimates of N₂O emissions and SOC change.

Table S3 Grain sorghum feedstock and conversion cost estimates.

Table S4 Sweet sorghum feedstock and conversion cost estimates.