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Managing Land Use Change Greenhouse Gas Emissions of Bioethanol Production

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Indirect land use change (iLUC) must be considered for bioconversion technologies. These technologies, such as corn-to-ethanol technologies, require land not only for the processing facility but also indirectly require land for the cultivation of the input biomass. There are greenhouse gas (GHG) emissions associated with the transformation of the required land, such as forests or pastures, into cropland for the input biomass. iLUC emissions and effects have been examined on a cursory level in the literature, but deeper analysis is needed. We present an iLUC life cycle optimization model that integrates cutting-edge iLUC modeling techniques with optimization methodology. The model minimizes total GHG emissions, composed of direct and indirect processing emissions as well as iLUC emissions of the chosen biofuel production strategy. A case study considering production of 37.9 BL/y of bioethanol in the U.S. illustrates that iLUC emissions contribute to the life cycle GHG emissions of biofuels, even in optimal scenarios. The minimum realizable iLUC emissions rate is 1.5 g CO_2-eq/MJ at this production level using corn stover as a feedstock.

1. Introduction and Background

Biofuels are an important component of a renewable energy strategy (Yue et al., 2014). Life cycle greenhouse gas (GHG) emissions of biofuels are potentially lower than those of petroleum-based fuels (You et al., 2012). However, important drawbacks exist with biofuels (Alwi et al., 2016). Some biofuels cause indirect land use change (iLUC), and these concerns guide feedstock selection as well as biofuel process selection and design (Gong and You, 2015). Emissions due to LUC might severely diminish the environmental benefit gained from biofuels over conventional fuels (Plevin et al., 2015). Calculating the LUC emissions of biofuels is an active area of research. Many researchers present wide ranges for LUC emissions of certain biofuels. Recent estimates for LUC emissions of corn ethanol range from 7.6 (Canter et al., 2015) to 53 g CO_2-eq/MJ (Plevin et al., 2015). These estimates guide global energy legislation. Minimizing the uncertainty involved in LUC emissions of biofuels by establishing a lowest realizable emission rate aids policymakers, industrialists, and scientists (Santibañez-Aguilar et al., 2015). Minimizing life cycle GHG emissions of biofuels must also include these emissions (Yue et al., 2013). iLUC emissions characterization and estimation methods are now quite advanced. The most sophisticated and advanced methods for estimating iLUC emissions from biofuels are based on computable general equilibrium (CGE) models. CGE models are highly detailed economic models of a large-scale economy. Transactions and taxes between regions, firms, households, and governments in a number of economic sectors are accounted for. Price elasticities of commodities and factors of production are also in the model. Users of a CGE model can “shock” the initial, stable economic equilibrium by changing some variables, for example, increasing biofuel production in the US Solving the model with the shock means searching for a new equilibrium state. Economic equilibrium occurs when there are zero profits, zero surpluses, zero shortfalls, and zero losses among all agents in the economy and when market prices of all goods equal their production costs. A CGE model is useful when characterizing and estimating iLUC effects. One can identify the initial land type and use distributions, introduce the shock, solve for the new equilibrium, determine the new land type and use distributions, and infer what changes must have happened. Next, land carbon stocks and soil organic carbon (SOC) levels combined with the land use changes can be used to calculate LUC emissions.

The most advanced iLUC characterization models use the Global Trade Analysis Project (GTAP) CGE model and data. The GTAP model is one of the most advanced CGE models of the global economy (Hertel, 1997). Taheripour et al. (2007) pioneered its use for calculating iLUC emissions of biofuels using computable general equilibrium (CGE) models (Taheripour et al., 2007). The Carbon Calculator for Land Use Change from Biofuels Production (CCLUB), developed by the U.S. DOE (Dunn et al., 2013), and an approach centred on a Net Displacement Factor (NDF) and IPCC carbon stocks data developed by Plevin et al. (Plevin et al., 2015) later built on this foundation and added other biofuels and feedstocks. Thanks to these advances, the uncertainty gap for the iLUC emissions rate of biofuels has narrowed. However, this type of method cannot determine an optimal biofuel production strategy that limits iLUC emissions. It can only determine the iLUC emissions for a given biofuel production scenario. Additional economic sectors must be added for each new biomass feedstock and ethanol production method. This requirement necessitates a variety of economic assumptions about the new sectors, increasing model uncertainties and computational burdens. We integrate cutting-edge iLUC calculation methodology into a life cycle optimization (LCO) framework (You and Wang, 2011), in order to produce an LUC LCO framework with 5 possible biomass feedstocks and 14 ethanol production options based on an existing bioconversion network (Garcia and You, 2015). This new framework allows us to circumvent previous uncertainties in biofuel iLUC emissions studies by integrating all equations and data into a single model. A minimum iLUC emissions rate from biofuels strategy is determined within the context of the global economy. The model also sets a lower bound on the iLUC emissions rate of biofuels. These new capabilities allow for more informed, targeted biofuel production policies and analysis of the life cycle emissions of biofuels. In the next section, we discuss the model's formulation. We then present a case study where the U.S. produces 37.9 BL of ethanol per year. We discuss the results of this case study and state the conclusions.

2. Problem Statement

The authors modeled a bioethanol production quota in the U.S. of 37.9 BL/y to be met with any biomass feedstock and any production pathway. Life cycle emissions, including LUC emissions, direct processing emissions, and indirect processing emissions are to be minimized. We assume that all biomass feedstock must be produced on new cropland (except stover), no region may more than double its biomass production, LUCs occur immediately, regions cannot create/lose land, biomass yields on new croplands start at the same level as previous yields in that region, only pasture and forest may be converted to cropland, and new biomass cannot be grown in regions where it was not initially grown. Major decision variables include which of the fourteen biofuel production pathway(s) to utilize, which of the 5 kinds of biomass to use, where to source the biomass for biofuel from the 19 regions, what kind of land to convert, and how much of each type of land to convert in each region. GTAP variables include commodity and factor prices, factor transformations, regional account balances, regional output as well as commodity export and import rates. Figure 1**Error! Reference source not found.** shows a visualization of this problem statement.

3. Methodology

Integrating an LCO framework with the GTAP model requires a variety of tasks and datasets. We briefly cover here GTAP, land use, and land value data, and the integration of a LUC LCO model based on GTAP into an optimization framework. Data on the different production pathways were obtained from various peer-reviewed literature (Gong et al., 2016). The production pathways chosen are as follows: for corn, traditional dry milling and wet milling to ethanol (Accardi et al., 2015); for sugarcane, the traditional process. For stover, the pretreatment methods differed: dilute acid (DA) pretreatment, two-stage DA pretreatment, AFEX pretreatment, and hot water pretreatment to distillation were considered (Humbird et al., 2011). Two more stover pathways of DA pretreatment to pervaporation and DA pretreatment with separate C5/C6 fermentation to distillation are also included (Kazi et al., 2010).

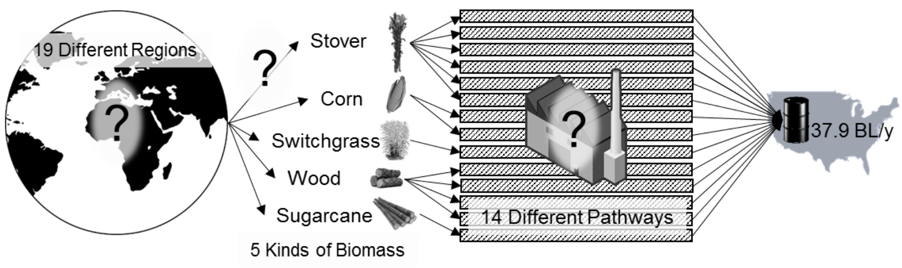

Figure 1. Visualisation of the problem statement

DA pretreatment of switchgrass to distillation is considered. Gasification of wood chips to mixed alcohol synthesis or acetic acid synthesis and hydrogenation round out the pathway options. The authors used the seventh version of the GTAP database which contains data for 112 regions and 57 sectors from 2004. 73 model equations comprise GTAP. The authors do not list them all here. They can be found in (Hertel, 1997). Many of the equations involve bilinear and/or nonconvex functions. For example, consider the unit cost function for endowment commodities f for sector g in region r:

$$CF_{gr} = \left(\sum_{f} \theta_{fgr}^{f} \cdot \left(PPF_{fgr} \right)^{1-\eta} \right)^{1/(1-\eta)}, \forall g, r \tag{1}$$

$CF_{g\,r}$ and PPF_{fgr} are variables, and **η** is a price elasticity factor that can range anywhere between zero and a large positive number. The above nonlinear and nonconvex equation is a typical CGE model equation. Other unit cost functions calculate the unit cost of a bundle of domestic and imported commodities within a region where multiple commodity price variables are multiplied together, creating bilinear or trilinear terms. Integration of CGE equations will result in a large-scale nonlinear programming (NLP) problem.

GTAP data is constantly updated, and users augment the model with data relevant to what they wish to study, but the core model equations do not change. The authors aggregated all data into 19 regions and 26 sectors, following the aggregation routine of previous iLUC research (Taheripour et al., 2007). Some regions include the U.S., EU-27, Brazil, etc., and some sectors include cereal grains, chemicals, sugarcane and sugar beet, etc. The authors followed Rutherford's (2006) method to integrate the GTAP model into an optimization model. Following previous iLUC research, we assume ethanol produced from biomass will be part of the "chemicals, rubber, plastic products" sector. Integration of the GTAP database and model equations into an LCO framework involved data collection, modifying the core GTAP equations and data, and formulating a LUC calculation module that can be seamlessly

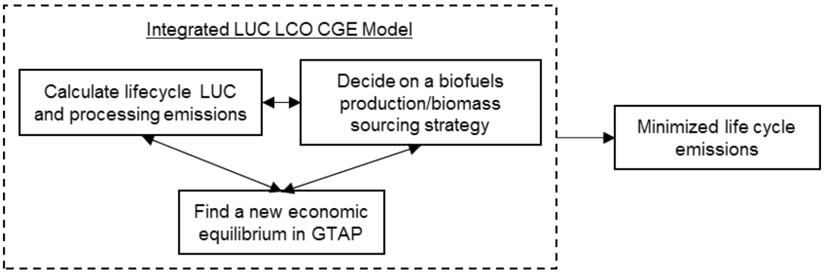

Figure 2: Visualization of the integration of GTAP and LCO modelling frameworks

integrated into the GTAP model. The core GTAP database has a single "Land" factor of production and does not include data related to land use, such as land cover, land type distribution, and economic values of different kinds of land. These data were taken from a number of sources, and integrated into the model. Land is divided into 18 Agro-Ecological Zones (AEZ) and 7 land types. The land types considered in this work include cropland, forest, pastureland, shrub-land, savannah/grassland, built-up land, and other unusable land. We expanded the core parameters to account for the 18 new AEZs instead of just one land factor of production. We also obtained data on the total cultivable land in each region.

An iLUC LCO model was constructed to be integrated with the GTAP model, formulated below. A visualization of how the models interact is in Figure 2. Capitalized terms are variables, lowercase terms are parameters:

min IP+DP+LP

$$\text{s.t. } TNL_{lfr} = \sum_{j} NL_{lfrj}, \forall l, f, r \tag{2}$$

$$TLL_{lfr} = \sum_{j} LL_{lfrj}, \forall l, f, r \tag{3}$$

$$\sum_{l} TLL_{lfr} = \sum_{l} TNL_{lfr}, \forall f, r \tag{4}$$

$$\sum_{l} TLL_{lfr} \le \sum_{l} ld_{lfr}, \forall f, r \tag{5}$$

$$\sum_{cropland} \sum_{f} \left(TNL_{lfr} - TLL_{lfr} \right) \le tcl_{r}, \forall r \tag{6}$$

$$cs_{cj} \cdot \left(\sum_{c}\sum_{x} C_{frcx} \cdot N_{cr} \cdot iby_{crf} - \sum_{corn}\sum_{x} C_{frcx} \cdot N_{cr} \cdot ddgs \cdot iby_{crf} \right) \le NL_{lfrj} \cdot cs_{cj}, \forall f, r, j, l = cropland \tag{7}$$

$$\sum_{r} G_r = \sum_{f}\sum_{r}\sum_{c}\sum_{x} C_{frcx} \cdot py_{cx} \tag{8}$$

$$\sum_{r} G_r = fdem \tag{9}$$

$$\sum_{x}\sum_{stover} C_{rfcx} \le 0.33 \cdot \left(sm_{rf} + \sum_{x}\sum_{corn} C_{rfcx} \cdot iby_{crf} \right), \forall r, f \tag{10}$$

$$\sum_{r} G_r \cdot fpr = \sum_{crp}\sum_{r} E_{gr} \tag{11}$$

$$N_{cr} = 1 \Big/ \left(1 + \sum_{g} \left(P_{gr} - 1 \right) \cdot ype_r \right), \forall c, r \tag{12}$$

$$CE = \left(\sum_{l}\sum_{f}\sum_{r} TLL_{lfr} \cdot \left(soc_{lfr} \cdot (1 - slf_{lfr}) + soc_{lfr} \cdot (1 - slf_{lfr}) \cdot sslf_{lfr} / (1 - sslf_{lfr}) + unc_{lfr} \right) - TNL_{lfr} \cdot npp_{fr} \right) \cdot cef \tag{13}$$

$$NE = \left(\sum_{l}\sum_{f}\sum_{r} TLL_{lfr} \cdot soc_{lfr} \cdot \left(1 - slf_{lfr} \right) \cdot cnf \right) \cdot nef \tag{14}$$

$$FE = \left(\sum_{Forest}\sum_{f}\sum_{r} TLL_{lfr} \cdot fg_{lfr} \right) \cdot cef \tag{15}$$

$$NL_{lfrj} \ge ld_{lfr} \cdot slm_{lj} \cdot \left(FT_{fr} \cdot \left(PS_{fjr} / PF_{fr} \right)^{\eta_{fr}} - 1 \right), \forall l, f, r, j \tag{16}$$

$$LL_{lfrj} \ge -ld_{lfr} \cdot slm_{lj} \cdot \left(FT_{fr} \cdot \left(PS_{fjr} / PF_{fr} \right)^{\eta_{fr}} - 1 \right), \forall l, f, r, j \tag{17}$$

$$Y_{gr} \cdot vom_{gr} = P_{gr} \cdot E_{gr} + \left(RA_r / P_{Cr} \right) + vom_{Gr} + vom_{Ir} + \sum_{i=g} DDFM_{igr} + \sum_{s} DXMD_{irs} + dst_{ir}, \forall g, r \tag{18}$$

$$LP = \left(CE + NE + FE \right) / tf \tag{19}$$

$$IP = \sum_{r}\sum_{f}\sum_{c}\sum_{x} C_{rfcx} \cdot ipe_x \tag{20}$$

$$DP = \sum_{r}\sum_{f}\sum_{c}\sum_{x} C_{rfcx} \cdot dpe_x \tag{21}$$

where set I,g,j represent GTAP commodities/sectors, l is the set of land types, f is the set of AEZs, r is the set of regions, c is the set of biomass feedstocks, and x represents the set of ethanol production pathways.IP represents the indirect processing emissions, DP the direct processing emissions, and LP the LUC emissions. TNL_{lfr} represents the total new land, and TLL_{lfr} represents the total lost land. NL_{lfrj} is the amount of new land used by sector j, and LL_{lfrj} is the amount of lost land that is no longer available to sector j. $ld_{lfr}$is the original land distribution, tcl_r is the total cultivable land of each region, cs_{cj} is an indicator that ties crop c to sector j, $C_{frcx}$is the mass of crop c grown in AEZ f in region r used in ethanol production pathway x. $N_{cr}$is the change in crop yields due to yield price elasticity. $iby_{crf}$is the yield of biomass feedstock, ddgs is the yield of ddgs in corn to ethanol processes, G_r is the volume of ethanol produced in region r, py_{cx} is the process yield for converting crop c into ethanol in pathway x, and fdem is the volumetric quota for bioethanol. sm_r is the maximum amount of stover that can be harvested sustainably, fpr is the price of bioethanol (in 2004 USD), $E_{gr}$is the value of ethanol produced, P_{gr} is commodity price, and ype_r is yield price elasticity. CE represents the CO_2-eq emissions from SOC loss, SOC loss from the subsoil, and from uncombusted biomass, npp_{fr} is the net primary productivity of land, soc_{lfr} is the SOC level of the original land, slf_{lfr} is the SOC loss factor, $sslf_{lfr}$ is the subsoil SOC loss factor, $uncc_{lfr}$ is the mass of uncombusted biomass, and cef is the CO_2-eq emission factor. NE represents the CO_2-eq emissions from changes in soil composition, cnf is the C : N soil ratio, and nef is the N_2O CO_2-eq emissions factor. FE is the amount of foregone CO_2 sequestration from forest growth, represented by fg_{lfr}. slm_{lj} denotes which sectors use which types of land, FT_{fr} represents factor transformation price changes; PS_{fjr} and PF_{fr} denote sector-specific factor prices and regional factor prices, and η_{fr}^{ae} is a factor price elasticity. vom_{gr}, RA_r, $DDFM_{igr}$, $DXMD_{irs}$, and dst_{ir} stand for total value of output at market prices, the regional account balance and market prices, the change in demand for commodity i, the change in exports/imports, and demand for international transportation services. Finally, ipe_x is the rate of indirect processing emissions of production pathway x and dpe_x is the rate of direct processing emissions of production pathway x.

Constraint (4) states that the total land lost in AEZ f in region r must equal the total land repurposed in that AEZ and region. Eq(7) – Eq(12) determine how much of each type of biomass to grow in each region for use as a biofuel feedstock. The authors assumed 33 % of the corn stover may be harvested sustainably in constraint

Eq(10). Constraint Eq(12) determines changes in crop yields in response to crop price changes. Eqs(12), (13), and (14) calculate LUC emissions based on changes in SOC, uncombusted biomass, and foregone forest sequestration. Constraints Eq(16) and Eq(17) state that the amount of each type of land gained or lost must be consistent with changes in demand for each type of land. Constraint (18) "shocks" the economy with production of bioethanol. Eq(19), Eq(20), and Eq(21) calculate LUC emissions, and indirect/direct processing emissions.

4. Results and Discussion

All experiments were performed on a DELL OPTIPLEX 790 desktop PC with an Intel(R) Core(TM) i5-2,400 CPU @ 3.10 GHz and 8 GB RAM. All models and solution procedures were coded in GAMS 24.7.1. The NLP consisted of more than 36,000 equations and 192,000 variables. There were over 440,000 nonlinear terms. The problem was solved with the KNITRO 10.0.1 solver to local optimality with feasibility tolerances of 10^{-5} and optimality tolerances of 10^{-4}. The case study was solved within 420 CPU s.

The demand of biofuel exactly equalled the required supply/quota of 37.9 BL/y. Two-stage dilute acid pretreatment and AFEX pretreatment of corn stover are the main chosen processing pathways to make the bioethanol. The emissions distribution for the case study is shown in Figure 3. Indirect emissions are negative due to sales of electricity from the process to the grid, displacing some energy input mix at the power plant. We assume the electricity that the plant displaces is generated from the average mix of the US electricity sources. Net emissions are also negative at -4.1 g CO_2-eq/MJ. Small capacities of other technologies are also chosen to meet the increased production of each feedstock from the modelled economic shock. Corn stover is collected from the US (60 Mt), the EU (12 Mt), Brazil (7 Mt), and the China + Hong Kong region (23 Mt). iLUC emissions account for 1.5 g CO_2-eq/MJ of life cycle emissions, and direct processing at the facility contributes 5.2 g CO_2-eq/MJ. 196,000 ha across the globe of pastureland and 8,100 ha of forests are converted to cropland. The additional cropland is largely cultivated to accommodate the increase in demand of various crops due to the increase in ethanol production. Prices of all commodities around the world rise slightly, increasing food prices slightly, and galvanizing additional crop production.

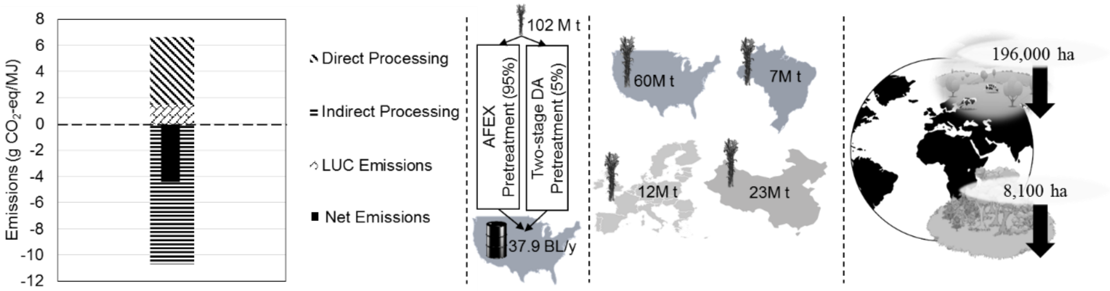

Figure 3. Results of the case study

Corn stover is the key feedstock as iLUC emissions of corn stover are marginal. No new cropland was needed – the current supply of corn stover in the large corn-producing regions is enough to produce 37.9 BL/y ethanol. Tthe iLUC emissions of corn stover ethanol represent the emissions from LUC brought about by changes in the economy. The LUC emissions rate of 1.5 g CO_2-eq/MJ is in line with previous estimates. The estimate is on the lower end of the estimates presented by previous studies, which is not surprising considering our goal is minimization of emissions. Importantly, the life cycle GHG emissions are dominated by direct processing emissions and indirect processing emissions. The results provide two key findings. One, the iLUC emissions rate of corn stover is low. Second, if minimization of life cycle emissions is the goal, then more focus must be directed towards more efficient and cleaner processing methods, as direct processing emissions are more than three times larger than iLUC emissions. The process also produces extra electricity. If this electricity is used to sequester or capture CO_2-eq emissions, then life cycle GHG emissions could decrease even further. Large decreases in forest cover for the U. (~ 7,000 ha) and Russian Federation (~16,000 ha) were observed. Afforestation occurred in Canada (~ 8,000 ha) as well as South and Other Americas (~3,000 ha). Conversion of pastureland in the U.S. (~125,000 ha), Brazil (~5,000 ha), China and Hong Kong (~3,000 ha), and South and Other Americas (~3,000 ha) to cropland, was by far the largest contributor to LUC. Price increases in cropping sectors outpaced those of livestock and animal product sectors, so the conversion of pastureland to cropland is expected. These anticipated changes in land use guide policymakers and relevant industries on what to expect. The more knowledge different actors in the biofuels life cycle have, the better they will be able to understand LUC effects of biofuels, and they will be better able to mitigate these effects. This model provides an optimal scenario for the LUC emissions of biofuels, so results can be seen as a "best case" scenario.

5. Conclusion

A novel land use change (LUC) life cycle optimization (LCO) modelling framework was developed. This model integrated LCO methodology with state-of-the-art LUC emissions characterization and calculation techniques. These techniques included the use of computable general equilibrium (CGE) models to determine LUCs before and after some economic shock. In this case, the economic shock was an increase in ethanol production. Five different biomass feedstocks and fourteen different ethanol production pathways were considered. Production of ethanol via two-stage dilute acid pretreatment and AFEX pretreatment and upgrading of corn stover was shown to have the lowest life cycle greenhouse gas (GHG) emissions at 37.9 BL/y US bioethanol. iLUC emissions from this scenario accounted for 1.5 g CO_2-eq/MJ, and direct processing emissions contributed 5.2 g CO_2-eq/MJ. This result signals that improvements in processing efficiencies and/or emissions reduction technologies could have the largest impact on minimizing life cycle emissions of biofuels. The net emissions rate was -4.2 g CO2-eq/MJ, stemming from a GHG emissions “credit” by selling excess electricity produced back to the electrical grid. The developed model laid the groundwork for future, more detailed studies on the iLUC emissions of biofuels and other products and processes.

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