The Lifecycle Carbon Footprint of Biofuels

January 29, 2008

Miami Beach, FL

The Lifecycle Carbon Footprint of Biofuels

Proceedings of a conference January 29, 2008, in Miami Beach, FL.

Edited by

Joe L. Outlaw

Agricultural and Food Policy Center
Texas A&M University
College Station, TX

David P. Ernstes

Agricultural and Food Policy Center
Texas A&M University
College Station, TX

Sponsored by

Farm Foundation
USDA's Office of Energy Policy and New Uses
Global Change Program Office, USDA Office of the Chief Economist

75 Farm Foundation
SINCE 1933

Environmental Lifecycle Assessment for Policy Decision-Making and Analysis

Deepak Rajagopal and David Zilberman[1]

Introduction

A key argument in the societal debate against polices to support biofuels is that production of these alternative fuels may in fact consume more energy than they generate and emit more greenhouse gases than they sequester (Fargione *et al*., 2008; Searchinger *et al*., 2008; Rajagopal and Zilberman, 2007; Farrell *et al*., 2006; Pimentel and Patzek, 2005). Metrics like net energy value, net carbon value and net petroleum offset are the basis for comparing the various fuels and are the source of these debates. The technique that underlies the calculation of these metrics is called lifecycle assessment or lifecycle analysis (LCA).

A central aspect of LCA (described in detail in the next section) is it assumes linear technologies and produces outcomes that are numbers – how many units of energy are needed to produce a liter of ethanol fuel from a ton of corn. But as basic economics suggests, under reasonable conditions of some substitution between inputs and processes in production, this ratio is not a number but a function of prices. For instance, with energy being a ubiquitous input to production, a change in the relative price of different energy sources or with respect to other inputs will induce adjustments in the form of fuel switching, substitution between capital, energy and labor etc. This switching can occur at several levels in the production chain of a commodity. This will obviously alter the net carbon indicator for a fuel in the future.

Also current LCA outcomes change only if the physical quantities of various inputs such as quantity of coal or electricity used in calculating LCA change. In other words, today LCA is capable of answering, *how does a 10% decrease in the share of natural gas in the average electricity mix decrease the net carbon value of ethanol*? But it is not capable of answering, *if natural gas prices increase by 10% what is the impact on the net carbon value of ethanol*? Obviously the latter is more intuitive and useful way of framing the question than the former from a policy standpoint. In this paper, we introduce a framework which can be used to derive LCA indicators directly as a function of underlying economic parameters and make it easier to simulate the impact of policies like pollution taxes and fuel mandates which in one way or another ultimately alter the relative price of commodities.

Next we provide some background on current LCA literature. We then introduce a micro-economics based LCA that integrates prices directly into the lifecycle framework. We point out some implications of our model with simple illustrations. We finally describe directions for future work.

LCA Models

LCA is a systems approach to evaluating the environmental footprint of products, materials, and processes (Hendrickson *et al*., 2006; Joshi, 1999; Lave *et al*., 1995). The goal behind the development of LCA was to quantify the resource and environmental footprint of a product over its entire lifecycle from raw material extraction, manufacturing, and use until ultimate disposal. By resource footprint, we mean the total physical flow of both extractive resources such as materials, energy, water etc. and polluting resources like green house gases, criteria air pollutants, toxic chemicals etc. through the various stages of the lifecycle. These physical values are then related to ultimate environmental burdens like global warming, acidification, smog, ozone layer depletion, eutrophication, deforestation etc. using established scientific relationships between emissions and impact.

It is useful to distinguish between aggregate LCA (that uses past data to convey the amount of GHG or other energy or pollutants generated on average in producing one unit of output – be it biofuel or other products in the whole economy) versus process specific LCA (that calculates the net amount of GHG associated with producing biofuel at a certain facility using a certain process from a crop grown in a certain way). Because of heterogeneity among locations in terms of productivity of corn, energy used to produce fertilizer, and energy sources for processing ethanol from corn, one would expect differences in the GHG footprint of ethanol across locations. Figure 1 shows a simplified representation of production of ethanol using two different pathways. Panel A shows a biofuel crop grown on existing crop land using gas-based fertilizers which is converted into biofuel in natural gas powered biorefinery. Panel B shows a biofuel crop grown on cleared forest land using coal-based fertilizer which is converted to biofuel in a coal powered biorefinery.

[1] Rajagopal is a PhD candidate, Energy and Resources Group, University of California, Berkeley. Zilberman is a professor in the Department of Agriculture and Resource Economics and a member of Giannini Foundation at the University of California, Berkeley.

If we assume that clearing forestland releases above-ground carbon stored in biomass and soil carbon and given that coal is more polluting than gas, biofuel produced through pathway (A) has a smaller carbon footprint than (B).

Either way we can get a number that will inform us of the GHG footprint of biofuel production in the past or the present. But when it comes to the future, things depend on economic and technological conditions. To elaborate on this point, note that businesses pursue profits, and their selection of technologies and input use varies according to economic conditions. Processors that convert corn into biofuels may choose from two sources of energy – coal and natural gas. An increase in the price of natural gas will lead to a switch to coal, which will result in a significant increase in the GHG generation associated with the production of ethanol. Thus, LCA should produce not just numbers but functional relationships.

But before we discuss extensions to LCA, we summarize the different LCA approaches in use today. Depending on whether the assessment is based on aggregate data or on a specific combination of technologies, there are two different types of LCA, namely, Environmental Input Output Life Cycle Assessment (EIOLCA) and process based LCA.

Environmental Input Output Lifecycle Assessment (EIOLCA)

The EIOLCA approach computes the environmental emissions associated with production of a given value of a good, say, $1 million worth of steel or electricity. It does so by tracing out the various economic transactions related to production like manufacturing, transportation, mining and related requirements etc. that would take place in order to produce the given value of the good. This information is derived from the economic input/output table of the economy. Several countries in the world routinely produce such input/output models.

In the United States, the Department of Commerce (DOC) maintains a 491 sector industry input-output (IO) model of the US economy i.e., an IO table which has 491 rows and columns. The EIO model is a representation of an economy in which the rows and columns in the table represent the various sectors of the economy and the entries in the tables represent total sales from one sector to others, purchases from one sector, or the amount of purchases from one sector to produce a dollar of output for the sector.

The EIOLCA model has been used to calculate the environmental impact of major industrial products like steel, concrete, automotive fuels, etc. (Hendrickson *et al*., 2006; Joshi, 1999; Lave *et al*., 1995). While simple and intuitive, this approach has a few drawbacks. Since it assumes fixed proportions in production (Leontief production), it does not allow for substitution between inputs within a given sector. While this is not unreasonable in the short-run it is not a plausible assumption in the longer run or medium run. For example, farmers may use less tilling or irrigation and use more land in response to higher energy prices. Such effects cannot be captured in this framework. Fertilizer and energy industries may also switch from gas to coal in the medium to long term in response to high oil prices or vice versa in response to a carbon pollution tax. Second, this approach computes the average effect rather than the marginal effects which are also more important from a policy stand point.

Process LCA

The process approach to LCA, contrary to the EIOLCA approach, emphasizes detailed modeling of each and every process in the production chain (Hendrickson *et al*., 2006). For example, in the case of biofuel production, process LCA would distinguish between irrigated and non-irrigated cultivation, between low-till and regular till farming, between dry-mill and wet-mill fermentation of corn to ethanol, etc. This approach is therefore useful when analyzing the environmental impact of a specific production chain or for analyzing emerging products

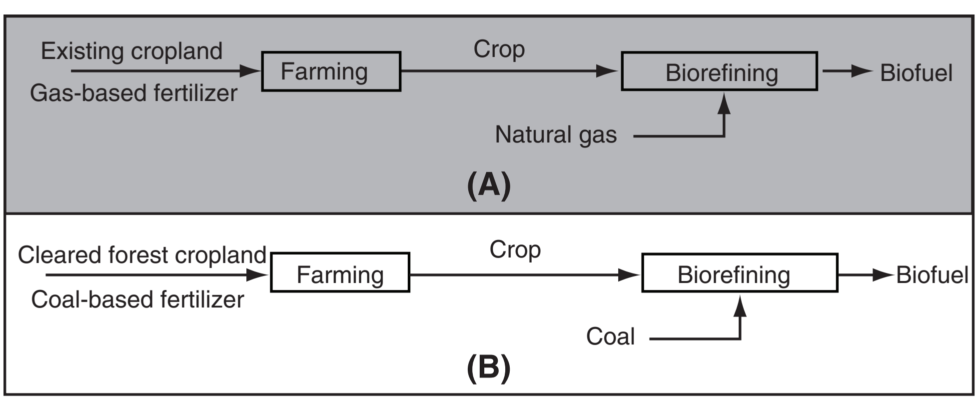

Figure 1: Two Possible Pathways of Producing Biofuel.

Table 1: Sensitivity of Ethanol LCA to Fuel Mix.

	Scenario	Kilograms of CO_2 eq. offset per liter of ethanol	Percent change over baseline
1	Baseline (Farrell *et al.*, 2006)	0.18	---
2	Net GHG displacement if average biorefinery uses only coal based energy	0.09	-50%
3	Net GHG displacement if average fertilizer production facility uses only coal based energy	0.07	-61%
4	Net GHG displacement if both the average biorefinery and fertilizer producer use only coal	-0.01	-106%
5	Net GHG displacement if average biorefinery uses only gas based energy	0.42	133%

and technologies – the effects of which are likely to be marginalized when one deals with industry wide aggregate data. For example, the LCA of cellulosic ethanol or the LCA of gasoline produced from tar sands is difficult to model using the EIO tables because these are not major economic activities in their respective sectors today. Process LCA has been the main technique behind the major assessments of biofuels thus far (Farrell *et al*., 2006; Tilmann *et al*., 2006; Pimentel and Patzek, 2005).

Sensitivity of LCA Outcome to Assumptions

Based on a meta-analysis of the various process LCA models of corn ethanol, Farrell *et al*. (2006) report that, on average, each liter of corn ethanol produced in the United States displaces 0.18 kilograms of carbon dioxide equivalent emissions. Their conclusion is based on the assumption that the average conversion facility derives 60% of is input energy from coal and 40% from natural gas. We performed sensitivity analysis of their model to various assumptions about the relative mix of coal and gas based energy input to corn conversion and fertilizer production. The results are shown in Table 1. In the extreme case when both biorefineries and fertilizer production shifts entirely to coal there is a net increase in GHG emissions from using corn ethanol compared to gasoline. On the other hand if say in response to a carbon tax the average facility shifts entirely to natural gas then there is a 133% increase in the estimated lifecycle GHG benefit.

Motivation for an Expanded LCA

The above illustration highlights the fact that the average biofuel's lifecycle indicators are a function of the choice of technology and other inputs of the average producer whose behavior is ultimately influenced by economic conditions. LCA numbers are therefore not an outcome of assumptions about just technology but also implicit assumptions about behavior and economic conditions. If economic conditions are expected to lead to the introduction and adoption of cellulosic technologies and adoption of wind power in a biofuel-producing region, then the GHG emissions from biofuel production within the region would decline (see Figure 2). Likewise farm policies that induce adoption of yield-increasing technologies in production of feedstocks (improved varieties, precision farming methods, etc.) would reduce GHG associated with the cultivation. Speaking of farm policies, land use effects are perhaps the most important and uncertain aspect of the lifecycle calculations. We discuss this next.

Land Use Effects and LCA

LCA was developed to assess the environmental impact of industrial processes. One of the challenges in applying it to biofuels is adapting this technique for agricultural systems. Production of biofuels may either directly or indirectly induce conversion of land from one form of use to another. When biofuels are produced by converting rangeland to farmland, the direct land effect is the resulting decrease or increase in carbon sequestration in soil and above-ground biomass. When lands that provided corn for food are converted to biofuels production, the reduced supply of corn will increase corn price and will lead to expansion of corn acreage. This extra land has an indirect effect on the GHG emission associated with the biofuels production.

A study by Fargione *et al*. (2008) finds that producing biofuels by converting forests or rangeland releases 17 to 420 times more GHG than the reduction these biofuels would provide by displacing fossil fuels. Searchinger *et al*. (2008) conclude that large scale expansion of biofuel production will cause expansion of agriculture into land currently not farmed, resulting in a net increase in carbon emissions for up to five decades before there is net sequestration. A closer look suggests that estimating emissions from land-use change is complex for a few reasons. The land expansion estimates are sensitive to assumptions about the type of crop and yield of biofuel per hectare, the type of lands into which agriculture expands, the role of policies and induced innovation that can raise the yield of food crops etc. The GHG contribution of the cleared biomass depends also on how it is managed. This contribution may be smaller when the cleared trees are used to generate power, thus replacing fossil fuel, or converted to products like furniture than when they are burned outright. The indirect effects are complex and depend on interaction among several markets, innovations in new technologies, and government policies. Since the indirect effect depends on complex economic factors, their incorporation into LCA requires incorporating general equilibrium effects in LCA which we discuss next. Allocation of emissions from land use change across time is another issue to consider.

General Equilibrium and LCA

The introduction of biofuels in the United States has expanded total corn acreage but diverted corn away from food and feed. The expanded corn acreage may take land away from lower value crops, which may move into marginal land which is not farmed today. In Brazil, grazing activity displaced in the Cerrado region by sugarcane expansion may encroach into the Amazon, although sugarcane may not be directly cultivated in the Amazon. Thus, when one considers the overall effect of producing biofuels on a large scale on net GHG emissions, the indirect land-use effect has to be taken into account. However, calculation of these effects is tricky.

Historically, food price increases have induced innovations and investments that increased productivity that slowed expansion of agricultural acreage. If rising food prices reduce barriers and accelerate introduction of new high yield varieties, the land expansion resulting from higher food prices is likely to decline. By lowering gasoline prices, biofuels could also delay the production of liquid fuels from dirtier fossil sources like tar sands and coal. However, technological lock-in into certain types of biofuels may also hinder development of cleaner alternative fuels.

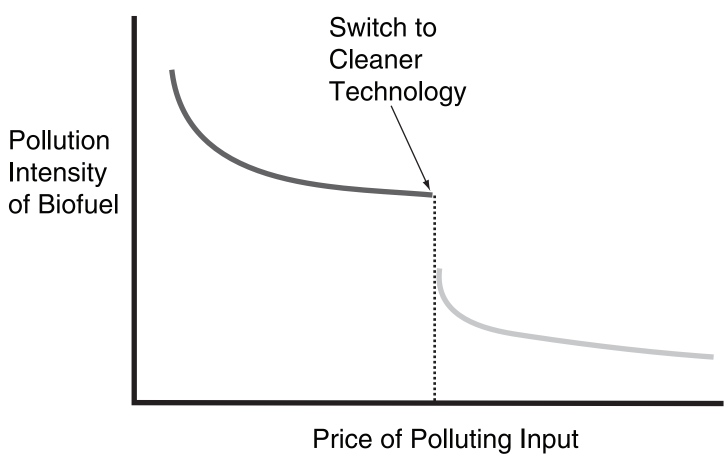

Figure 2: Adoption of Cleaner Technologies for Biofuels at High Carbon Price.

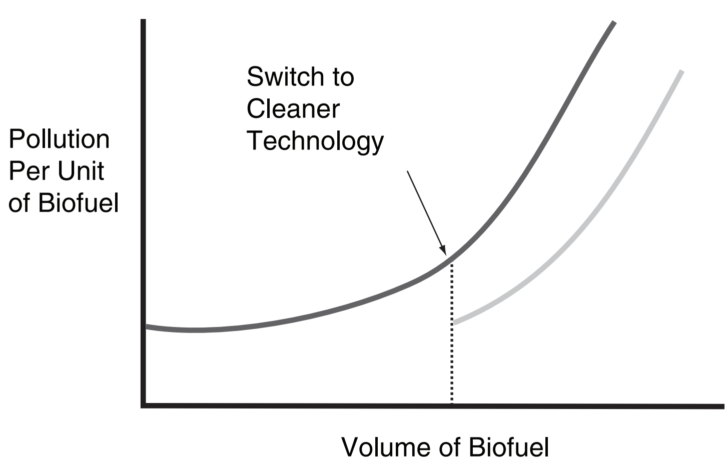

Figure 3: Impact of Scale on Pollution Per Unit of Biofuel.

Such intricate linkages call for careful interpretation of current LCA numbers. If one conducts LCA on activities that are done on a relatively small scale or products with small markets, then general equilibrium effects can be ignored. Otherwise secondary effects associated with changes in prices have to be taken into account. When conducting a general equilibrium analysis to assess the aggregate GHG impact of biofuel, especially when looking at the future, one has to recognize that this effect depends on policies. Introduction of policies that will invest in research to improve the productivity of biofuels and the efficiency of processes that convert them to fuels, or policies that will enhance the adoption of biotechnology of similar productivity-enhancing technologies in traditional agriculture may lower the impact of biofuels on GHG.

Summary of LCA

In summary LCA indicators can vary depending on the assumptions about the following underlying factors:

1. ***Aggregation:*** Depending whether the LCA is done on an economy-wide basis or done for a specific production pathway using detailed assumptions about the inputs and technologies at each stage – indicators will vary. EIOLCA is an aggregate LCA. Process LCA, on the other hand, can be used to model either a specific pathway or the average case for a niche or emerging market.
2. ***Time:*** Indicators will vary depending on whether one is modeling expost or ex-ante. Ex-ante LCA is more challenging since the future is uncertain, being dependent on policies and technological change among other things. A common mistake that is committed is in using ex-post LCA to make predictions about the ex-ante using assumptions such as fixed coefficients in production etc.
3. ***Scale:*** One can easily identify several reasons why the carbon footprint of biofuels can vary depending on the scale of production. For example, biofuel expansion may induce agricultural expansion into marginal land which may involve greater carbon emission per unit of biofuel. Large scale production may also induce adoption of more efficient technologies which have scale economies (see Figure 3) lowering the pollution intensity. Benefits may also accrue in the form of efficiency gains from learning-by-doing. This highlights the risk of extrapolation using fixed coefficients over a large range. Figure 4 depicts another case in which depending on the marginal pollution intensity of the biofuel, the pollution intensity of the average fuel may increase or decrease. Marginal pollution intensity

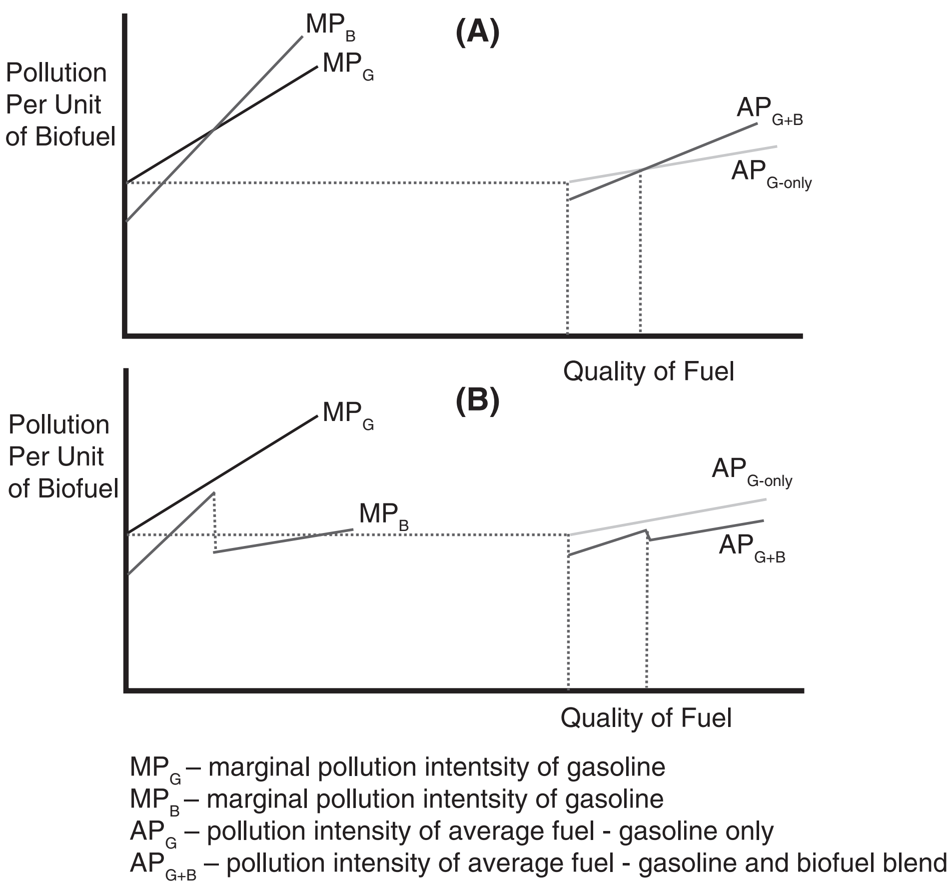

Figure 4: Implication of Relative Marginal Pollution Intensities of Gasoline and Biofuel for the Average Pollution Intensity of Fuel.

of gasoline is expected increase with the introduction of tar sands and coal liquefaction.

4. ***Policies:*** When performing ex-ante LCA it is important to recognize that policies that affect the incentives for producers may lead to investment in and adoption of technologies that will enable adaptation to policy. For example, subsidies for research and development (R&D) may lead to development of high yielding biofuel crops and high efficiency conversion technologies while emission taxes can induce the intensity of coal use in the economy to decrease.

A Microeconomics-Based LCA Technique

The choice of inputs and technologies reflects producer behavior and therefore a good prediction should combine the technical and behavioral aspects of production. Economic research has developed theories of production that allow choices and use economic conditions to determine what exactly is selected. But current LCA does not permit choices (Delucchi, 2004) nor models the economic considerations explicitly. In one of the earliest works that combine a *process LCA-like* material balance model with an economic model of production and consumption, Ayres and Kneese (1969) outline a general equilibrium framework in which the flow of services, materials and pollutants are accounted for and related to welfare. The motivation for their model was the recognition that it is important to develop a method for forecasting pollution from a system wide perspective at the scale of regional or national economy much like the motivation of LCA today. But the drawback of their approach was that they assumed fixed proportions for production within each sector. This limits the usefulness of having prices embedded in the model, since it does not permit any adjustment in input ratios as a function of relative prices.

A Simple Model of Biofuel Production

We now illustrate using a simplified representation of biofuel production (shown in Figure 5), how a parametric relationship between input prices and lifecycle emissions can be derived. We assume that ethanol, is produced with two inputs namely, corn and energy. Corn in turn is produced using two inputs namely, land and energy. Finally, energy can be produced from two different sources with different carbon intensities, say gas and coal. The former is generally considered a less polluting fuel relative to coal. In order to keep the mathematical exposition simple and intuitive, for now, we do not consider other essential inputs like capital or labor or other forms of energy. We also assume that all producers are price-takers in both input and output markets and maximize profit. In the next section we generalize the results to an arbitrarily large model with more than two inputs and multiple stages in the lifecycle.

In Figure 5:

Y_f	quantity of biofuel produced;
X_p	quantity of plant matter required to produce the given quantity of biofuel;
X_e	quantity of energy required to convert plant matter to biofuel;
X_l	quantity of land to produce the required quantity of plant matter;
X_{e1}	quantity of energy required to produce the required quantity of plant matter;
X_c, X_g	quantity of coal and gas required to produce the required quantity energy for conversion;
X_{c1}, X_{g1}	quantity of coal and gas required at the farm phase to produce plant matter;
Z_p	pollution from farming;
Z_f	pollution from conversion of plant matter of biofuel.

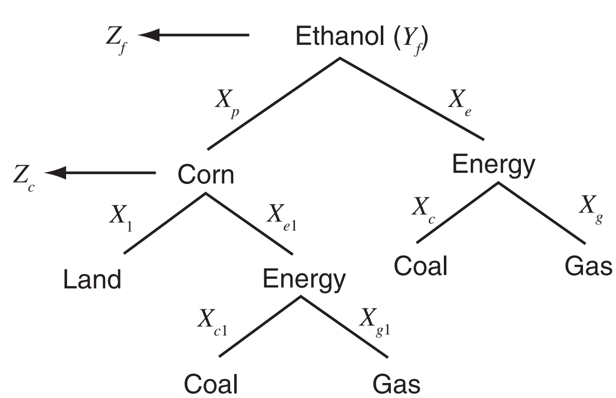

Figure 5: A Simple Model.

Production Functions The production relationships for the system shown in Figure 5 are given by:

$Y_f = F_f(X_p, X_e)$

$X_p = F_p(X_1, X_{e1})$

$X_e = F_e(X_c, X_g)$ and $X_{e1} = F_e(X_{c1}, X_{g1})$

$Z_f = G_f(X_c, X_g)$

$Z_p = G_p(X_{c1}, X_{g1})$

with, $F_i' > 0,\ F_i'' < 0,\ G_i' > 0,\ G_i'' = 0$ (linear pollution function).

Then $\Gamma_f = Z_f + Z_p$ denotes the total lifecycle emission associated with a quantity Y_f of biofuel while, $\frac{\Gamma}{Y_f}$ denotes the emission intensity of biofuel.

But in reality corn is produced in much larger quantities than that used for biofuel production. Let us say a fraction a_{pf} of the total corn production is utilized for biofuel production. Then Z_p is a certain fraction of the total emissions associated total corn production in the economy *i.e.*, $Z_p = a_{pf}\Gamma_p$, where Γ_p is the total lifecycle pollution associated with corn farming in the economy. Therefore,

$$\Gamma_f = Z_f + a_{pf}\Gamma_p \tag{1}$$

Pollution Generation Function For simplicity we will assume that pollution arises solely from the use of energy and not other inputs. In other words, we ignore for now pollution that may result from land preparation processes like tilling or from conversion of land away from other previous uses. Also let the pollution function G be linear in inputs. That is,

$$G_f(X_c, X_g) = b_c \times X_c + b_g \times X_g \tag{2}$$

$$G_p(X_{c1}, X_{g1}) = b_c \times X_{c1} + b_g \times X_{g1} \tag{3}$$

where, b_c, b_g are emission coefficients for coal and gas respectively.

Since $Z_f = G_f(X_c, X_g) = b_c \times X_c + b_g \times X_g$ differentiating with respect to p_c we get,

$$\frac{dZ_f}{dp_c} = b_c\frac{dX_c}{dp_c} + b_g\frac{dX_g}{dp_g} \tag{4}$$

Relationship Between Input Price and Emissions if Production Function is Cobb-Douglas Given these assumption we derive the mathematical relationships between the relative price of energy inputs and emissions from production of biofuel. The implications of relaxing one or more of these assumptions is described later. If production can be represented by a constant elasticity of substitution (CES) function we can write,

$Y_f = [(\alpha_p X_p)^{\rho f} + (\alpha_e X_e)^{\rho f}]^{1/\rho f}$

$X_p = [(\alpha_l X_l)^{\rho l} + (\alpha_{e1} X_{e1})^{\rho l}]^{1/\rho l}$

$X_e = [(\alpha_c X_c)^{\rho 1} + (\alpha_g X_g)^{\rho 1}]^{1/\rho 1}$

$X_{e1} = [(\alpha_{c1} X_{c1})^{\rho 2} + (\alpha_{g1} X_{g1})^{\rho 2}]^{1/\rho 2}$

where,

$\rho = \frac{1}{1 - \sigma}$ and σ is the elasticity of substitution between inputs.

The CES functional form nests the common functional forms such as Cobb-Douglas (CD), linear production and the Leontief production functions. When $\sigma = 1$, CES reduces to CD. We know that for a CD production function, the cost minimizing factor demands are given by,

$$x_i^* = x_i^*(\vec{p}_i, P, Y) = \frac{\alpha_i PY}{pi} \tag{5}$$

where,

x_i^* optimal level of input use

$\vec{p}_i$ vector of price of inputs

Y - quantity of output

P - output price

α_i - exponent for the i^{th} input in the CD production function with $\sum_{i=1}^{n}\alpha_i = 1$ since we have assumed CRS technology.

Differentiating Equation 5 with respect to p_j we get,

$$\frac{dx_j^*}{dp_i} = \alpha_i\frac{x_j^*}{p_i} \text{ if } i \neq j \ \& \ \frac{dx_i^*}{dp_i} = -(1 - \alpha_i)\frac{x_i^*}{p_i} \tag{6}$$

Substituting for $\frac{dx_i^*}{dp_i}$ from Equation 6 into Equation 4 we get,

$$\frac{dZ_f}{dp_c} = -b_c(1 - \alpha_c)\frac{X_c^*}{p_c} + b_g\alpha_c\frac{X_g^*}{p_c} \tag{7}$$

Table 2: Sensitivity of Ethanol LCA to Fertilizer Price Doubles.

Exponent for fertilizer in farm production (input parameter)	0.1	0.2	0.35
Percent increase in farm emissions when fertilizer price doubles	9%	17%	26%
Percent change in net GHG benefits per liter of ethanol	-11%	-17%	-22%

And substituting the expression for X_c^* and X_g^* from Equation 5 we get,

$$\frac{dZ_f}{dp_c} = \alpha_c [\alpha_g \frac{b_g}{p_g} - (1 - \alpha_c)\frac{b_c}{p_c}]\frac{P_f Y_f}{p_c} \qquad (8)$$

A similar relationship can be derived for $\frac{dZ_p}{dp_c}$, the change in pollution for corn production with a change in price of coal.

Differentiating Equation 1 with respect to p_c we get,

$$\frac{d\Gamma_f}{dp_c} = \frac{dZ_f}{dp_c} + \frac{d}{dp_c}(a_{pf}\,\Gamma_p) \qquad (9)$$

If we assume a_{pf} the proportion of total corn output flowing into ethanol does not change, substituting Equation 8 into Equation 10 we get,

$$\frac{d\Gamma_f}{dp_c} = \alpha_c \frac{1}{p_c}[\alpha_g \frac{b_g}{p_g} - (1 - \alpha_c)\frac{b_c}{p_c}](P_f Y_f + \alpha_{pf} P_p X_p) \qquad (10)$$

Similarly,

$$\frac{d\Gamma_f}{dp_g} = \alpha_g \frac{1}{p_g}[\alpha_c \frac{b_c}{p_c} - (1 - \alpha_g)\frac{b_g}{p_g}](P_f Y_f + \alpha_{pf} P_p X_p) \qquad (11)$$

Equations 10 and 11 show the relationship between the change in lifecycle emissions and with a change in price of one of the inputs for a given level of output Y_f of biofuel. Given our assumptions about competitive behavior and CRS technology, input factor intensities are constant at any level of output and since pollution function is linear in inputs, therefore emissions scale linearly with level of output. If on the other hand the various factors are perfect substitutes then we can expect discrete shifts when relative price exceeds a certain threshold. Similar relationships can be derived for other production relationships like generalized CES, Leontief etc. The mathematics is straightforward but unwieldy and hence we do not derive it here.

Illustration of Increase in Fertilizer Price on Carbon Emissions from Corn Production Let us assume that corn is produced using four inputs, namely, land, fertilizer, irrigation and labor and that pollution is caused only from fertilizer use and irrigation only. We assume a Cobb-Douglas form for agricultural production and a linear pollution function.

$$X_{corn} = f(X_L, X_F, X_I, X_l) = AX_L^{\alpha L} X_F^{\alpha F} X_I^{\alpha I} X_l^{\alpha l}$$

$$Z_{corn} = b_F * X_F + b_I * X_I$$

where, X_{corn} - output of corn; Z_{corn} - carbon emissions due to corn production; L - land; F - fertilizer; I - irrigation; l - labor; α_i - elasticity of output for the i^{th} input, b_F and b_I - carbon intensity of fertilizer and irrigation respectively.

For simplicity let us assume fertilizers are produced from natural gas while irrigation is using coal-based electricity. (This is not an unrealistic unassumption because more than 90% of fertilizers in US are gas-based while electricity in the Midwest is dominated by coal and the carbon intensity of these inputs is the carbon intensity of natural gas and coal respectively. Of course, the results derived below hold only for irrigated corn production.) Using an expression similar to that in Equation 10 and rewriting in terms of elasticities we can derive the percent change in emissions from corn production. We then use these results in the model of Farrell *et al*. (2006) to predict the percent change in net GHG benefits of corn ethanol as fertilizer prices increase.

Table 2 shows our estimates for three different elasticities of corn output to fertilizer input. Obviously since an increase in fertilizer price leads to substitution of fertilizer with other inputs which has a higher carbon intensity there is a net increase in lifecycle emissions and a decrease in the carbon offset by each liter of ethanol.

Application to Analysis of Pollution Tax Policy We now show how pollution taxes can be easily incorporated into our model. Let us say there is a tax of $\$\phi$ per unit of pollution Z rising from the production at any stage. Then the cost minimization problem can be written as:

$$C = min(\vec{p}^T\vec{X} - \phi Z_k) = min((\sum_{j=1}^{n} p_j X_j) - \phi Z_k) \qquad (12)$$

If pollution function Z is linear in inputs, *i.e.*

$Z = \sum_{j=1}^{n} b_j X_j$, we can rewrite the above equation as

$$C = min\sum_{j=1}^{n}(p_j - \phi b_j)X_j = min\sum_{j=1}^{n}\tilde{p}_j X_j \qquad (13)$$

Table 3: Sensitivity of Ethanol LCA to Carbon Tax on Coal and Gas.

Carbon tax ($/ton)	5	10	15
Percent increase in relative coal price	17%	35%	57%
Percent change in net GHG benefits per liter of ethanol	117%	228%	383%

where, $\tilde{p}_j = p_j - \phi b_j$, is the effective price received by producers.

We now simulate the effects of a carbon tax on net GHG benefits of corn ethanol. Let us again assume that both corn production and conversion can be represented by a Cobb-Douglas production function. Table 3 shows the sensitivity of benefits for three different levels of a carbon tax.

The model can thus be extended in a straight forward way to include policies like pollution taxes, production subsidies, and import tariffs etc., all of which exist especially in the case of ethanol or biodiesel. The effect of a change in the level of a policy tool can therefore be easily analyzed by changing the coefficients in the model. This model can be easily extended to a general setting involving an arbitrary number of production processes and inputs in the lifecycle.

Modeling Issues for Future Consideration

The purpose of the simple illustration was to bring out the intuition behind our approach to incorporate economic parameters into environmental lifecycle analysis. We assumed a simple neoclassical production function and perfectly competitive structure in input and output markets. In future research we will demonstrate how we can model to incorporate:

1. Other representations of production: Putty-clay technology with discrete adoption, other functional forms for neoclassical production.
2. Heterogeneity: Variations in land quality, etc.
3. Industry structure: Monopoly, monopolistic competition, oligopoly.
4. Behavior: Profit maximization, risk aversion.
5. Regulation: Emission tax, emission standard, quantity mandates, tradable emission permits.
6. Innovation, learning and technological change

Conclusion

We are at a critical moment when several state and national governments are debating decisions about how to regulate the carbon intensity of their energy sources. Since continuous monitoring of carbon emissions from each production site is costly, tools like LCA can be valuable in providing the necessary information about relative carbon intensities of different energy sources to policy makers. But as it stands today, LCA is an ex-post accounting analysis while from a regulatory standpoint LCA requires an ex-ante estimation capability. So a better understanding of how carbon and energy footprints will change in different economic and policy scenarios will result in better incentives and better policy-making.

We described how LCA indicators can vary depending on the level of aggregation, the time horizon, scale of production, and economic and policy incentives faced by producers who face a choice of technologies. Current LCA approaches are either opaque or are not flexible when it comes to allowing such considerations. In this regard, taking into account prices and their impact on choice will allow more accurate assessment of environmental impact. The first basic improvement we suggest is to make lifecycle indicator to be a function of prices. We showed how one can derive the functional relationships under standard assumptions like well behaved neoclassical production and pollution functions and that capital is malleable and all inputs are generic.

We have also identified several possible extensions to the basic model we intend to purse as part of future work. Although the emphasis has been on the application to biofuel production and greenhouse gas emissions, the framework is more broadly applicable to analysis of any industrial or agricultural production and other pollutants. Due consideration should be given to non-GHG environmental impacts that would result from biofuels. In the authors' opinion, these have not received adequate attention in the LCA literature.

Acknowledgements

This work was partially funded by a grant from the Energy Biosciences Institute at the University of California, Berkeley.

References

Ayres, Robert U. and Allen V. Kneese. "Production, Consumption and Externalities." *The American Economic Review* 59(3)(June 1969): 282-297. [Accessed April 30, 2008.] Available from http://www.jstor.org/sici?sici=0002-8282(196906)59%3A3%3C282%3APCAE%3E2.0.CO%3B2-K

Delucchi, Mark A. *Conceptual And Methodological Issues In Lifecycle Analyses Of Transportation Fuels*. UCD-ITS-RR-04-45. Davis, CA: University of California-Davis, October 2004. [Accessed April 30, 2008.] Available from http://www.its.ucdavis.edu/publications/2004/UCD-ITS-RR-04-45.pdf

Fargione, Joseph, Jason Hill, David Tilman, Stephen Polasky and Peter Hawthorne. "Land Clearing and the Biofuel Carbon Debt." *Science* 319(5867)(February 29, 2008): 1235-1238. [Accessed April 30, 2008.] Available from http://www.sciencemag.org/cgi/content/full/319/5867/1235

Farrell, Alexander E., Richard J. Plevin, Brian T. Turner, Andrew D. Jones, Michael O'Hare and Daniel M. Kammen. "Ethanol Can Contribute to Energy and Environmental Goals." *Science* 311(5760)(January 27, 2006): 506-508. [Accessed April 30, 2008.] Available from http://www.sciencemag.org/cgi/content/full/311/5760/506

Hendrickson Chris T., Lester B. Lave and H. Scott Matthews. *Environmental Life Cycle Assessment of Goods and Services: An Input-Output Approach*. Washington, DC: Resources for the Future, April 2006.

Joshi, Satish. "Product Environmental Life-Cycle Assessment Using Input-Output Techniques." *Journal of Industrial Ecology* 3(2-3)(April 1999): 95-120. [Accessed April 30, 2008.] Available from http://www.blackwell-synergy.com/doi/pdf/10.1162/108819899569449

Lave L.B., Cobas-Flores E., Hendrickson C.T., McMichael F.C. "Using Economic Input-Output Analysis to Estimate Economy-Wide Discharges." *Environmental Science & Technology* 29(9)(1995): 420A-426A.

Pimentel, David and Tad W. Patzek. "Ethanol Production Using Corn, Switchgrass, and Wood; Biodiesel Production Using Soybean and Sunflower." *Natural Resources Research* 14(1)(March 2005): 65-76. [Accessed April 30, 2008.] Available from http://petroleum.berkeley.edu/papers/Biofuels/NRRethanol.2005.pdf

Rajagopal, Deepak and David Zilberman. *Review of Environmental, Economic and Policy Aspects of Biofuels*. Policy Research Working Paper WPS4341. Washington, DC: The World Bank Development Research Group, September 2007. [Accessed April 30, 2008.] Available from http://www-wds.worldbank.org/external/default/WDSContentServer/IW3P/IB/2007/09/04/000158349_20070904162607/Rendered/PDF/wps4341.pdf

Searchinger, Timothy, Ralph Heimlich, R.A. Houghton, Fengxia Dong, Amani Elobeid, Jacinto Fabiosa, Simla Tokgoz, Dermot Hayes and Tun-Hsiang Yu. "Use of US Croplands for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change." *Science* 319(5867)(February 29, 2008): 1238-1240. [Accessed April 30, 2008.] Available from http://www.sciencemag.org/cgi/content/full/319/5867/1238

Tilman David, Jason Hill and Clarence Lehman. "Carbon-Negative Biofuels from Low-Input High-Diversity Grassland Biomass." *Science* 314(5805)(December 8, 2006): 1598-1600. [Accessed April 30, 2008.] Available from http://www.sciencemag.org/cgi/content/full/sci;314/5805/1598?maxtoshow=&HITS=10&hits=10&RESULTFORMAT=&fulltext=%28Carbon-Negative+AND+Biofuels+AND+from+AND+Low-Input+AND+High-Diversity+AND+Grassland+AND+Biomass%29&searchid=1&FIRSTINDEX=0&resourcetype=HWCIT