Environ. Sci. Technol. **2011,** *45,* 132–138

Policy Implications of Uncertainty in Modeled Life-Cycle Greenhouse Gas Emissions of Biofuels[⊥]

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Received July 22, 2010. Revised manuscript received November 1, 2010. Accepted November 9, 2010.

Biofuels have received legislative support recently in California's Low-Carbon Fuel Standard and the Federal Energy Independence and Security Act. Both present new fuel types, but neither provides methodological guidelines for dealing with the inherent uncertainty in evaluating their potential life-cycle greenhouse gas emissions. Emissions reductions are based on point estimates only. This work demonstrates the use of Monte Carlo simulation to estimate life-cycle emissions distributions from ethanol and butanol from corn or switchgrass. Life-cycle emissions distributions for each feedstock and fuel pairing modeled span an order of magnitude or more. Using a streamlined life-cycle assessment, corn ethanol emissions range from 50 to 250 g CO_2e/MJ, for example, and each feedstock-fuel pathway studied shows some probability of greater emissions than a distribution for gasoline. Potential GHG emissions reductions from displacing fossil fuels with biofuels are difficult to forecast given this high degree of uncertainty in life-cycle emissions. This uncertainty is driven by the importance and uncertainty of indirect land use change emissions. Incorporating uncertainty in the decision making process can illuminate the risks of policy failure (e.g., increased emissions), and a calculated risk of failure due to uncertainty can be used to inform more appropriate reduction targets in future biofuel policies.

Introduction

Two pieces of legislation relevant to biofuels were recently passed in the United States: the 2007 Energy Independence and Security Act (EISA) and the 2007 California Low-Carbon Fuel Standard (CA LCFS) (*1*, *2*). The renewable fuel standard (RFS) included in EISA addresses both national security issues related to petroleum supply and the threats of anthropogenic climate change, specifying types of fuels, volumes required, and fuel life-cycle GHG reduction requirements. The life-cycle targets for expected corn and switchgrass ethanol emissions are 20% and 60% lower than gasoline, respectively. The CA LCFS requires the state fuel mix to have 10% lower emissions than would occur from fossil fuels alone by 2020 and promotes the use of life-cycle analysis to categorize acceptable fuel−process combinations. These acts require only the use of point estimates of emissions for each fuel classification, which reflects historic trends in the literature for biofuel life-cycle emissions calculations. Many studies aim to refine current models to produce increasingly precise emissions estimates, and mainly cover current- and near-term fuel types (primarily ethanol and biodiesel) and feedstocks (for example refs *3*−*6*). Encouragingly, several recently published studies have begun to address uncertainty in modeling biofuel systems (*7*, *8*). Both use Monte Carlo simulation as a tool to investigate the range of potential values for biofuel pathways and influential parameters in the model. Neither paper addresses indirect land use change (ILUC) or the policy implications of recent legislation given the uncertainty.

Although legislation acknowledges uncertainty and variation in input parameters, particularly related to land use change emissions, no quantitative methodology to deal with the uncertainty is prescribed. This is troublesome for two reasons: first, using only single values disregards the ranges and uncertainty of data used to generate the point estimate (such as a mean value), and second, new fuel life cycles can only be predicted, not measured.

Based on trends in biofuel research, new fuel life cycles will need to be evaluated in the near future. This next generation research generally addresses two topics: new fuel types and nonfermentative production methods (*9*−*13*). These papers reveal that longer-chain alcohols, particularly butanol and its isomers, are attractive alternatives to ethanol due to higher energy density (28 MJ/L LHV versus 21 MJ/L for ethanol) and greater compatibility with current fuel distribution infrastructure. The literature also describes how modifying microbial metabolism can produce these new fuel types. These novel production methods have little to no production-scale data (particularly at mandated fuel volumes), making life-cycle emissions difficult to predict and their contribution to compliance with renewable or low-carbon fuel standards even more difficult to forecast.

This paper uses a streamlined life-cycle emissions model with Monte Carlo simulation to quantify the uncertainty in life-cycle GHG emissions associated with ethanol and butanol production from both corn and switchgrass feedstocks. The focus of this work is not to put forth a set of emissions values or ranges but to raise discussion on the implications of basing policy on life-cycle emissions data or methods that are uncertain. Looking at the modeled distributions alongside a distribution for gasoline (the predominant fuel in the current mix) allows for a discussion surrounding the potential for increased biofuel emissions compared to gasoline, which represents a policy failure, and recommendations as to how the decision-making process might be improved by accommodating uncertainty.

Methods

Life-cycle assessment (*14*) allows for a holistic characterization of a process. This work utilizes a streamlined approach (*15*) focusing on the major life-cycle stages with respect to greenhouse gas emissions. This model considers six life-cycle stages: land use change; feedstock production; feedstock transportation; fuel production; fuel distribution; and fuel combustion. External life-cycle emissions from the fossil fuels and the nitrogen fertilizer used in the feedstock production

[⊥] This manuscript is part of the Environmental Policy: Past, Present and Future Special Issue.

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10.1021/es1024993

Published on Web 12/01/2010

and the fuel production stages are also included. The functional unit of this study is 1 MJ fuel produced.

The fuel production stage is central to this model, as the processes and resulting emissions depend on both feedstock and fuel. A thermodynamic model of maximum fuel yield from each feedstock provides a lower bound for feedstock quantity required per MJ fuel output. Contrasting these bounds with realistic fuel yields used in current models demonstrates the impact of technology and/or efficiency improvements on life-cycle emissions. To overcome the lack of production data for new fuels and production methods, production processes are based on currently modeled processes from the literature. Production energy demands are assumed to scale with fuel energy output. The upstream stages (land use change, feedstock production and transportation) depend only on feedstock type, with feedstock quantity depending on the thermodynamic model. Upstream emissions factors are taken from the literature. Downstream stages (fuel distribution and combustion) depend on fuel type. Emission factors are again taken from the literature. Life-cycle fossil fuel emissions factors are taken from Argonne's GREET model (*16*) and are common across all feedstock−fuel pairs to facilitate interfuel comparisons.

Five model runs are discussed in this paper. The first case is a set of point estimates used to obtain life-cycle emissions for the purposes of model calibration. The second uses parameter distributions for select input assumptions for use in Monte Carlo simulation (summarized in Supporting Information (SI) Table 7). The third is a modification of the Monte Carlo simulation (second scenario) that differs only in assuming maximum theoretical fuel yield values. The fourth is a modification of the second scenario that differs only in assuming a lower modal value in the switchgrass yield parameter distribution. The fifth scenario differs from the second only in excluding indirect land use change emissions (i.e., assuming zero ILUC emissions), while keeping the DLUC and carbon sequestration distributions.

Determining Fuel Yields. Biochemically converting feedstock to fuel can be broken into two steps: conversion of feedstock to sugar(s) (hydrolysis), and conversion of sugar to fuel (fermentation). Details, including sugar types and nonsugar components, are included in the Supporting Information.

In corn, starch can be hydrolyzed, or "cooked", using steam and amylase. In switchgrass, hemicellulose is separated from cellulose and hydrolyzed using some combination of steam and a dilute acid or base. An enzyme such as cellulase or a high-concentration acid solution catalyzes cellulose hydrolysis (*17*). This model assumes 90% yield (base case) of hydrolysate for both feedstocks. Once hydrolyzed, monomeric sugars can be converted to an alcohol (i.e., fuel) with an assumed 95% glucose conversion efficiency, and 85% efficiency for all other sugar types (*18*).

The fuel yield model for calculating maximum theoretical yields, by mass, is detailed in the Supporting Information. Ethanol has the highest theoretical mass yield at 51% and an energy density of 27 MJ/kg (LHV). Butanol has a lower mass yield of 41%, but a higher energy density at 33 MJ/kg.

Using corn as feedstock, ethanol requires 114 and butanol requires 115 g feedstock/MJ fuel (98 g/MJ with complete hydrolysis and fermentation). Using switchgrass, ethanol requires 129 and butanol requires 130 g/MJ, compared to 104 and 105 g/MJ fuel, respectively, under ideal yields. Feedstock mass requirements are approximately constant across these two fuel types (and across all simple alcohols, see SI Section 1). This has important implications for upstream greenhouse gas emissions. Feedstock quantity drives upstream emissions as well as emissions from the feedstock-to-sugar stages of fuel production.

Assuming average yields of 17 Mg dry matter (dm)/ha switchgrass (*19*) and 9.8 Mg dm/ha corn (*20*) and nonidealized hydrolysate and fuel yields, land requirements are approximately 0.01 m^2 corn/MJ fuel and 0.007 m^2 switchgrass/MJ fuel.

Land Use Change. Land use change resulting from biofuel life-cycle activities can be divided into two categories: direct land use change (DLUC) and indirect land use change (ILUC). These mechanisms are discussed in the Supporting Information.

For EISA, the EPA performed life-cycle assessments for both corn and switchgrass ethanol, among other feedstock−fuel pairs (*21*). Base case emissions factors for DLUC and ILUC for corn and ILUC for switchgrass are taken from this study, scaled based on increased fuel yield per hectare (89% for corn, 73% for switchgrass) to account for decreased land demand under higher feedstock yield and fuel conversion yields based on the assumptions made in this model. DLUC and ILUC emissions are 0.30 and 5.5 Mg CO_2e/ha/year respectively. Note that corn growth provides no soil carbon sequestration. This model takes switchgrass DLUC emissions to be a combination of direct conversion emissions from the California LCFS study (*22*), totaling 2 Mg CO_2e/ha/year, and a soil carbon sequestration value of 2 Mg CO_2e/ha/year from ref *19*. The assumed land use conversion and soil carbon sequestration emissions balance, which approximately matches the slight negative total calculated by the EPA study (*21*).

These land use emission factors are 30-year totals, undiscounted and amortized evenly over the time period (following Searchinger (*23*) and one EPA scenario). Time period and discount rate both impact land use emissions factors, but are not examined here (see *21* or *24* for an analysis of these variables).

Feedstock Production. GHG emissions result from fossil fuel consumption to power the harvesting process and from the production and use of fertilizers. Farming emissions are taken from the GREET model, totaling 46 g CO_2e/kg corn and 7 g CO_2e/kg switchgrass.

Fertilizer production is fossil fuel intensive, generating 3 kg CO_2e/kg N (*16*). Corn requires more fertilizer than switchgrass, averaging 150 kg N/ha (*25*) versus 74 kg N/ha (*26*). Fertilizer application produces N_2O emissions via direct and indirect mechanisms, here modeled based on IPCC definitions (see *27* and SI) and calculation methods. Emissions are 100 g CO_2e/kg corn and 68 g CO_2e/kg switchgrass, from IPCC eqs 11.6 and 11.7, using listed values for corn and field grasses (IPCC report Table 11.2), and assumed nitrogen application rates and feedstock yields.

Feedstock Transportation. This component uses GREET model values for both corn and switchgrass transportation from field to fuel processing plant (*16*). Transportation is by truck, and emissions are 22 g CO_2e/kg corn and 14 g CO_2e/kg switchgrass. Corn emissions are greater than those of switchgrass due to 25% greater transportation distances and the use of a less fuel-efficient vehicle for 20% of the distance.

Fuel Production. The production process varies by feedstock input and fuel output. As a result, modeling this life-cycle stage requires four semidistinct models for each of corn or switchgrass butanol or ethanol. Figure 1 shows process steps for fuel production for corn and switchgrass as feedstocks. Process steps unique to each fuel include fermentation and fuel concentration/purification. Differing enzyme activity for fermentation and differing degrees of fuel solubility in water necessitate unique concentration/purification activities and process energy. Calculation details are presented in SI.

The corn ethanol process is assumed to be the USDA's corn dry-grind model (*28*). Process electricity is from the grid and process heat is generated by natural gas combustion.

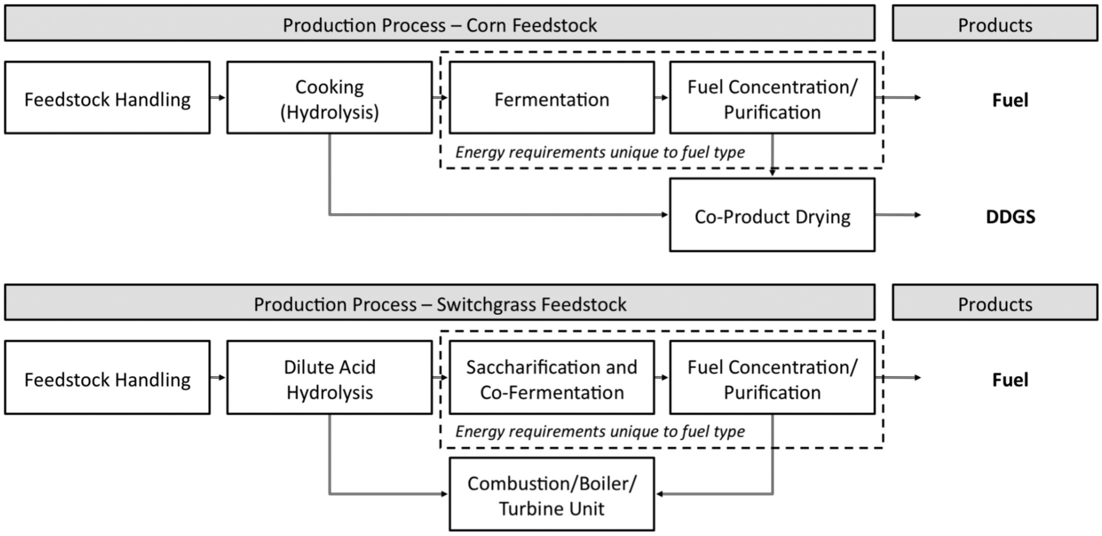

FIGURE 1. Fuel production processes. Arrows indicate mass flow.

To keep production systems between fuels as consistent as possible, the model maintains common process steps from the USDA model for butanol, replacing only the fermentation and fuel concentration/purification steps with those modeled by Wu (*29*). This model assumes butanol is the sole fuel produced (allowing a closer comparison with corn) whereas Wu's process yields acetone, butanol, and ethanol (ABE). ABE production process energy is used to approximate energy to produce maximum yield butanol. Total energy requirements are 0.46 MJ/MJ corn ethanol and 0.70 MJ/MJ corn butanol.

Production of fuel from corn yields distiller's dried grains with solubles (DDGS), a coproduct marketable as animal feed. Consistent with EISA and CA LCFS, system expansion is used (*14*) to model emissions credits for DDGS displacement of soy meal. This value is 15 g CO_2e/MJ fuel, taken as an average value from GREET and Biofuel Energy System Simulator (BESS) (summarized by *5*).

The switchgrass ethanol process is that of Aden et al. (*18*). Nonfermentable portions of the feedstock and unfermented sugars supply process energy; they are combusted to generate steam for process heat and to drive a turbine. This model uses a 68% efficient boiler to provide steam, with surplus heat going to drive an 85% efficient turbine. In the case of insufficient energy available from these switchgrass components, the model considers two sources of supplemental process energy: additional switchgrass fed directly into the boiler, or natural gas and grid electricity (as is the case for corn fuels). Emissions for switchgrass as an energy source are based on upstream emissions from this model, 0.1 kg CO_2e/kg switchgrass from base-case assumptions. In the case of excess electricity, surplus electricity is sold to the grid for credit (0.2 kg CO_2e/MJ).

Cellulosic butanol is possible (see *30*−*32*), but no large-scale production models currently exist. Butanol production energy requirements are estimated by taking Wu's fermentation and distillation energies and replacing those steps in Aden's model, adjusted to account for the saccharification of cellulose within the fermentation step. Total energy requirements for switchgrass ethanol are 0.58 MJ/MJ and 0.82 MJ/MJ for butanol.

Fuel Distribution. Postproduction emissions depend only on fuel type, not on feedstock. Point estimate GREET model values for modal distribution (e.g., train, truck) and fuel type consumed by mode were assumed (listed in SI Tables 5 and 6). Ethanol emissions are 1.2 g CO_2e/MJ, 20% greater than those of butanol per functional unit due to the higher volumetric energy density of butanol.

Fuel Combustion. Following prior work (*3*−*5*), we assume the only source of carbon in the fuel is from the source feedstock, which in turn was provided by environmental carbon, so the CO_2 released is assumed to replace exactly that which was used to produce the feedstock. Thus, net combustion emissions are zero.

Monte Carlo Simulation. The simulation methodology is guided by a well-known reference on uncertainty (*33*). Distributions are fitted when sufficient data available (e.g., crop yields) or assigned based on min/max and modal values to model parameters. Monte Carlo simulations enable an investigation into how input uncertainty propagates through the life-cycle emissions model. These distributions and underlying data sources are summarized in SI Table 7. The greatest uncertainty is associated with the land use change emissions, the N_2O emissions factors, and production emissions, where greater uncertainty is associated with the switchgrass and the butanol pathways, as fuels from switchgrass and butanol from any feedstock are currently unproven processes at any sort of large scale.

Results and Discussion

Model Calibration. Total point estimate emissions of 45 g CO_2e/MJ for corn ethanol, which excludes the land use stage, from this model are comparable to other studies with similar system boundaries (*5, 16*, and *34* find 41, 58, and 60 g CO_2e/MJ, respectively). Corn butanol emissions are about 20% higher than those of corn ethanol, which is consistent (though greater) with the difference in one other corn butanol LCA (*29*). Higher butanol life-cycle emissions are mainly due to higher fuel production emissions and a lower DDGS emissions credit compared to corn ethanol. The upstream stages for corn ethanol and butanol are common.

Simulation Results. Complete point estimate life-cycle emissions for each feedstock−fuel pathway are broken down by stage in SI Figure 4, with net emissions summarized in Table 1. Figure 2 shows PDFs for six combinations of feedstock, fuel type, and production energy source. Mean values are summarized in Table 1, and complete distribution statistics are included in SI Table 8.

Four cases for switchgrass (SW) as feedstock are investigated in this model: two using fossil fuels in the form of grid electricity and natural gas for heat (noted with [FF]) for production process energy, and two using the direct combustion of switchgrass for heat and electricity (noted with [SWf]). Switchgrass ethanol production sees an electricity surplus because the energy in the lignin and unfermented sugars is greater than the heat and electric energy required

TABLE 1. Summary of Total Emissions Resulting from Initial Point Estimate and Monte Carlo Simulation Scenarios

model (shorthand)	point estimate scenario emissions (g CO_2e/MJ)	mean emissions from Monte Carlo (MC) simulations			
		base MC scenario (g CO_2e/MJ)	MC with max fuel yield (g CO_2e/MJ (%))	MC with lower expected SW yield (g CO_2e/MJ (%))	MC with no ILUC (g CO_2e/MJ (%))
corn ethanol (corn etOH)	101	112	97 (−13%)[a]	n/a	63 (−44%)
corn butanol (corn buOH)	119	131	115 (−12%)	n/a	81 (−38%)
switchgrass ethanol, fossil fuel production energy (SW etOH [FF])	18	50	68 (+36%)	71 (+42%)	6 (−88%)
switchgrass ethanol, switchgrass production energy (SW etOH [SWf])	18	48	59 (+23%)	69 (+44%)	4 (−92%)
switchgrass butanol, fossil fuel production energy (SW buOH [FF])	48	90	98 (+9%)	112 (+24%)	46 (−49%)
switchgrass butanol, switchgrass production energy (SW buOH [SWf])	31	76	77 (+1%)	99 (+30%)	32 (−58%)

[a] Percentages in MC with max fuel yield, MW with lower SW yield, and MC with no ILUC are changes from the Base MC Scenario.

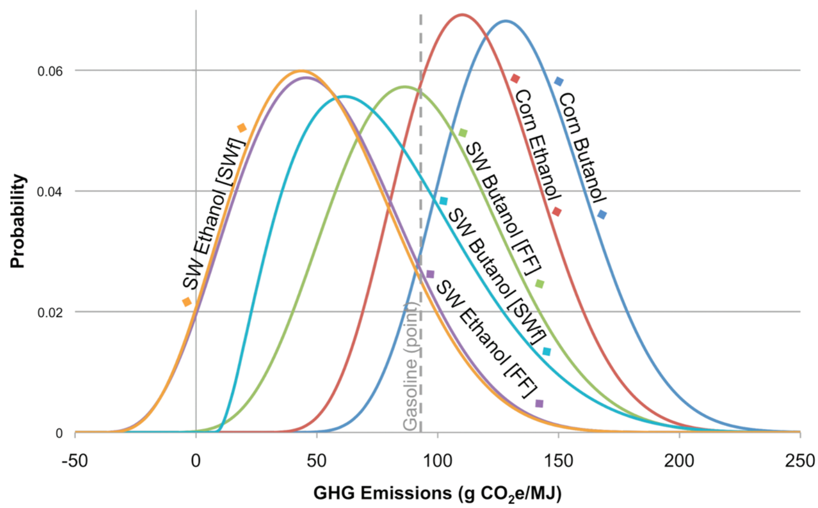

FIGURE 2. Probability distributions for total GHG emissions. Curve identifications list shorthand for feedstock type, fuel type, and fuel production energy source (if necessary) as listed in Table 1.

in the production process. As a result, the pathway has negative production emissions due to a grid electricity displacement credit. The SW EtOH [FF] and [SWf] cases are very similar because a supplementary source of energy is required only under a small set of simulated input values. Butanol production energy demand exceeds the amount available in lignin and unfermented sugars; therefore, external energy is required. Fossil fuel emissions factors (see the SI) are greater than that of switchgrass (0.01 kg CO_2e/MJ), accounting for the large production emissions difference between the two butanol cases.

Maximizing fuel yield presents diverging impacts for corn- and switchgrass-based fuels. As shown in Table 1 Column 3, mean GHG emissions decrease for corn by more than 10%. Upstream emissions decrease due to decreased land demands resulting from lower feedstock requirements. In contrast, GHG emissions for switchgrass-based fuels increase with increasing fuel yields. While upstream emissions decrease with decreased land demands, the unfermented sugars that provide process energy (and potentially an electricity displacement credit) vanish with maximum fuel yields. The result is that all feedstock-fuel pathways require supplementary process energy, thereby producing GHG emissions rather than receiving a GHG credit. The increased process emissions outweigh the decreased upstream emissions, resulting in increased total emissions for the switchgrass pathways.

The switchgrass emissions distributions are wider than those of corn due to greater uncertainty associated with this less proven cellulosic production pathway. This model assumes that the switchgrass distribution has the same negatively skewed shape as corn. When this distribution is adjusted to reflect lower yields found in the literature than assumed in the base case (assigning a new triangular yield distribution with lower bound 5.2 Mg/ha from *26*, mode 12.9 Mg/ha from *35* and keeping the upper bound constant), both the mean and variance of the output distributions for the switchgrass-based fuels are greater. Feedstock yield determines upstream emissions, which include the highly uncertain indirect land use change emissions (distribution mode adjusted to 2.3 Mg CO_2e/ha/year to account for the lowered yield), so changes here have substantial impacts on the expected life-cycle emissions, as shown in the mean value changes in Table 1 Column 4. SI Figure 5 shows the impact of the yield change on the switchgrass ethanol PDF. For switchgrass to provide convincingly low carbon fuels, yields must be carefully tracked because of their large impact on emissions calculations.

Model Sensitivity to Input Parameters. Table 2 shows the contribution to variance and the rank order correlation coefficient for the uncertain input parameters (above a 1% threshold) for the ethanol fuel pathways presented above. Butanol data are similar, and are included in the SI. If better characterized, this ordered list of influential parameters

TABLE 2. Percent Contribution to Variance (ConV) and Rank Order Correlation Values (ROCV) for Three Ethanol Pathways Considered

parameter	ConV (%)/ ROVC					
	corn ethanol		SW etOH FF		SW etOH SWf	
ILUC emissions factor	85.1%	0.91	66.2%	0.79	70.5%	0.81
DLUC emissions factor			4.6%	0.21	5.0%	0.22
soil C sequestration factor			2.8%	−0.16	3.0%	−0.17
direct N_2O emissions factor	4.1%	0.20	2.7%	0.16	2.9%	0.17
feedstock yield	6.7%	−0.25	1.8%	−0.13	1.9%	−0.13
production energy			17.0%	0.40	13.4%	0.36
glucose conversion efficiency	2.2%	−0.15				
hydrolysis efficiency			3.0%	0.17	2.0%	0.14

indicates emissions sources that offer the greatest opportunity to decrease the overall uncertainty associated with life-cycle biofuel emissions.

The ILUC emissions factor is overwhelmingly the key parameter for each scenario, due to both the high contribution to total emissions from ILUC and the high degree of ILUC uncertainty (i.e., wide distribution of possible values). Improving the economic models that forecast indirect land use change and associated emissions presents an opportunity to greatly increase the confidence with which we can predict biofuel emissions. This, of course, assumes ILUC uncertainty can be substantially reduced with better knowledge; some argue some of this uncertainty is irreducible, at least in the near future (*36*), so an emissions range that spans an order of magnitude may be the best one can anticipate.

The direct N_2O emissions factor plays a significant role in total emissions for all feedstock−fuel pathways. IPCC (*27*) is not the only source admitting uncertainty in N_2O emissions from nitrogen fertilizer. In a widely cited paper, Crutzen et al. suggest total N_2O emissions are 5−8% of applied N (by mass) (*37*), which is greater than the total using the IPCC 1% factor in each of the direct and indirect N_2O calculations. Using the ranges, rather than point estimates, listed in the IPCC report, this 5−8% range falls within the possible emissions in this model. So, it is really the mode that is controversial.

The only difference between the two switchgrass cases is the greater influence of the production energy parameter in the fossil fuel case (FF). This is a result of the grid electricity emission factor, as discussed above. Corn ethanol is more sensitive to corn yield than switchgrass (SW) fuels are to switchgrass yield, likely because of the increased upstream emissions from corn than from switchgrass.

The shape of each life-cycle emissions distribution (Figure 2) reflects the influence of these key parameters. For example, the ILUC emissions factors for corn are more symmetric than for switchgrass, which are positively skewed. There is corresponding symmetry and skew in distributions for corn fuels and switchgrass (SWf) fuels, respectively.

Policy Impacts of Uncertainty: EISA 2007 Renewable Fuel Standard. The distributions in Figure 2 show life-cycle emissions spanning more than an order of magnitude. This highlights the degree of uncertainty in biofuel emissions, particularly when indirect land use is considered. Making major policy decisions based on point estimates ignores this. Evaluations of relative fuel merit and predicted emissions reductions are less robust as a result.

Mean gasoline emissions from the EPA are 93 g CO_2e/MJ fuel (*21*). This is the baseline against which proposed alternative fuels are compared for the EISA, so corn-based and cellulosic fuels must be below 74 and 37 g CO_2e/MJ, respectively. CA LCFS gasoline life-cycle emissions are slightly higher at 95 g CO_2e/MJ (*38*). Looking solely at the difference between mean values over the full life-cycle evaluation (see Table 1, Column 2), corn fuel shows an increase in emissions over gasoline, and though the cellulosic fuels show emissions reductions, none meet the 60% reduction requirement.

A more complex and informative picture is painted when probability distributions associated with each fuel type, including gasoline, are considered. Figure 3 presents the likelihood that biofuel emissions will be less than or equal to the EISA target emissions levels (i.e., meet the target), defined as a percentage decrease from gasoline, as the policy target becomes more aggressive (i.e., as the percentage increases). Note the gasoline distribution used in this comparison is that of Venkatesh et al. (*39*) shifted so the mean matching the EPA value of 93 g CO_2e/MJ. Corn ethanol has a probability of lower emissions than gasoline of 0.1 (which is at the *y*-intercept, or the 0% point), and only a very small chance of meeting the 20% target. The fuel with the

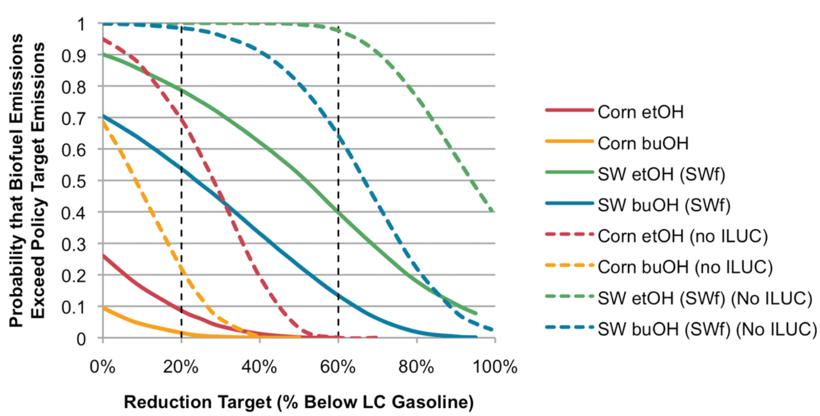

FIGURE 3. Probability that biofuel emissions are below those of gasoline (at 0%) or are below some policy target. EISA targets for corn fuels are 20% reduction and for cellulosic fuels are 60% (shown with vertical lines). Two modeled cases are presented: full life cycle and life cycle without ILUC.

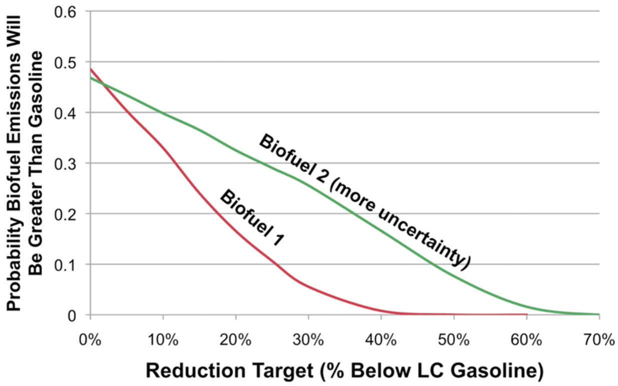

FIGURE 4. Probability that biofuel life-cycle emissions will be greater than those of the displaced fossil fuel given some required percentage difference between gasoline emissions and mean biofuel emissions (the reduction target). The probabilities are based on modeled emission distributions, Biofuel 1 shaped as corn, and Biofuel 2 shaped as switchgrass (wider, less certain distribution).

lowest GHG emissions, switchgrass ethanol (SWf), is very likely to have lower emissions than gasoline ($p = 0.9$) but it does not meet EISA target of a 60% decrease; the likelihood of lower emissions than the target is about 0.4.

Including indirect land use change emissions is controversial (see *40* for some discussion). If ILUC emissions are simply not included as part of the life cycle, as some proponents of biofuels suggest is the appropriate path, biofuels show greater promise to reduce GHG emissions. Table 1 (Column 2) shows that the mean emissions of four of six fuels meet the EISA reduction targets. Taking the distributions into account (Figure 3, dashed lines), a random gallon of corn ethanol has a probability of almost 0.7 of meeting the 20% reduction target. Switchgrass butanol shows almost the same probability of meeting its 60% reduction target, while switchgrass ethanol looks very likely to surpass the target. Removing ILUC emissions not only pulls two-thirds of the fuels into an acceptable category by mean comparison (see Column 5), but also demonstrates that these fuels can be accepted with a degree of confidence of at least 0.7 that the fuels do meet their respective targets.

ILUC emissions are of particular importance as they have the greatest influence on life-cycle emissions and will tip the decision for or against each of the ethanol types modeled here. ILUC, then, requires particular attention in order to reduce the possibility of making the wrong policy recommendation.

Policy Impacts of Uncertainty: Quantifiable Risk of Policy Failure. We conclude this paper with an illustrative hypothetical construct. Consider a case where the mean value for a fuel just meets some legislated percentage decrease (target) requirement from a life-cycle fossil fuel emissions value. This fuel would be accepted under legislation. However, with a high degree of uncertainty there is a possibility that the alternative fuel's emissions would be higher than the required target. Also, depending on the aggressiveness of the RFS or LCFS reduction target and the level of uncertainty surrounding the biofuel, there may be some probability that biofuel emissions are actually greater than those of the fossil fuel it intends to replace, thereby increasing emissions. This probability is shown in Figure 4 for two representative biofuels with differing distribution widths (Biofuel 2 being greater than Biofuel 1). These probabilities are obtained by shifting the biofuel distribution further from the fossil fuel distribution and calculating at each step the probability that the biofuel emissions are greater than the fossil fuel emissions. A failure of policy certainly occurs if emissions are greater with a biofuel than with the displaced fossil fuel. The policy could also fail if the reductions do not meet the required target.

This exercise demonstrates the required trade-off between policy aggressiveness and confidence in obtaining some reduction in emissions. A reduction target for Biofuel 1 of only 10% has a probability of increased emissions of 0.36, where a 20% target has a probability of only 0.13. The change in probability with change in percentage is a direct result of the shape of the emissions distributions for each biofuel, so a narrower distribution will yield a faster decrease in the probability of policy failure (or degree of confidence in policy success). Under current policies based on point estimates, a level of confidence in emissions reduction is an unintended consequence of the target reduction level (either on a per-fuel basis, or for the overall fuel mix).

Perhaps a more responsible policy design approach is to perform an uncertainty analysis (such as the Monte Carlo analysis demonstrated here) on the feedstock−fuel pathways of interest, choose an "acceptable" degree of confidence in reductions occurring (on the *x*-axis), and then legislate a corresponding percentage target (on the *y*-axis). This approach need not be restricted to biofuels policy. Uncertainty analyses of this sort can inform decision and policy makers whenever an incumbent is to be replaced by a new product. The uncertainties related to the incumbent's life cycle are often different than those related to the replacement, so each must be explicitly included for a reliable comparison to be made.

Acknowledgments

This research was made possible through support from the Climate Decision Making Center (CDMC) located in the Department of Engineering and Public Policy. This Center has been created through a cooperative agreement between the National Science Foundation (SES-0345798) and Carnegie Mellon University. The views stated are those of the authors and not of the National Science Foundation. Support has also been provided by the Betty and Gordon Moore Foundation, the Bertucci Fellowship, and the Energy Foundation. Assistance from Jeanne vanBriesen and Paulina Jaramillo is gratefully acknowledged.

Supporting Information Available

Yield calculations, details on the life-cycle fuel model, output statistics and assumptions for both point values and estimates, and input distributions. This material is available free of charge via the Internet at http://pubs.acs.org.

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ES1024993